COOPERATION AND LANGUAGE

Altruism in the emergence of linguistic capacity

MARIANO MORA MCGINITY

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Co-supervisor: Prof. Geraint Wiggins
Co-supervisor: Dr. Matthew Purver

School of Electronic Engineering and Computer Science
Queen Mary University of London

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ABSTRACT

This thesis investigates the effect of two different forms of cooperative behaviour on the emergence and evolution of language. A recent paradigm in evolutionary linguistics views language as a *complex dynamic system* whose emergence and development can be explained as the product of the interplay between cognitive, biological and social constraints. These researchers have generally acknowledged the vital role played by cooperation in the emergence of language: *homo sapiens* would not have developed language without a willingness to cooperate at levels which are particular to humans. Cooperation, however, is itself the subject of an evolutionary process, it is also an adaptive system.

There are many forms of cooperative behaviour. This thesis studies the impact on language of two opposing forms: *altruism* and *mutualism*. We define altruism as an individual's willingness to cooperate with another agent regardless of the cost to itself. On the other hand, an individual displaying mutualistic behaviour will decide to cooperate with another agent only if it can expect to obtain a benefit from the interaction.

The methodology in based on computer simulations of agents situated in an environment. The agents interact with each other, communicate about and perform costly joint actions, and are rewarded if they perform the action successfully. They do this by playing a *coordination language game*: an interaction model which allows us to measure the effect of environmental and communication costs on the emergence of a common language.

This document discusses the results obtained from two types of studies:

1. Type I investigates emergence of a common language in two separate populations, one made up exclusively of altruistic agents, while the other consists solely of mutualistic agents. Through this type of study we can observe whether, and under what conditions, language emerges in isolated populations.

2. Type II simulates emergence in a single mixed population, in which altruistic and mutualistic agents interact with each other. This allows us to investigate whether one type of behaviour will provide individuals with a fitness advantage.

Both types of study are used to simulate the emergence of:

- *holistic* languages, which map a single utterance to a whole meaning;

- *compositional* languages, in which the semantic value of the utterance is determined by the semantic value of its parts.

Results indicate a strong relation between costs and the effect of cooperative behaviour on the development of a common language. Neither strategy displays significant differences if environmental and communication costs are low with respect to the reward obtained. As costs increase altruistic agents develop a common language much faster than mutualistic agents, and altruism grants agents a selective advantage in terms of fitness. If the costs are too high, however, altruistic agents are penalised harshly, and mutualism becomes advantageous. In this case, populations do not develop a common language.

Su lenguaje y las derivaciones de su lenguaje – la religión, las letras, la metafísica – presuponen el idealismo. El mundo para ellos no es un concurso de objetos en el espacio; es una serie heterogénea de actos independientes. Es sucesivo, temporal, no espacial. No hay sustantivos en el conjetural Ursprache de Tlön, de la que proceden los idiomas "actuales" y los dialectos: hay verbos impersonales, calificados por sufijos (o prefijos) monosilábicos de valor adverbial. Por ejemplo: no hay palabra que corresponda a la palabra luna, pero hay un verbo que sería en español lunecer o lunar. Surgió la luna sobre el río se dice *hlör u fang axaxaxas mlö* o sea en su orden: *hacia arriba (upward) detrás duraderofluir luneció*. (Xul Solar traduce con brevedad: *upa tras perfluyue lunó. Upward, behind the onstreaming it mooned*.)

– Jorge Luis Borges *Tlön, Uqbar, Orbis Tertius*

Ein Wort, du weißt: eine Leiche

– Paul Celan

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ACRONYMS

CAS Complex Adaptive System

CLG Coordination Language Game

ESS Evolutionary Stable Strategy

ILM Iterated Learning Model

PAG Probabilistic Attribute Grammar

RNG Reciprocal Naming Game

1

INTRODUCTION

1.1 EVOLUTION AND EVOLUTIONARY LINGUISTICS

Herodotus tells us in his *Histories* (Herodotus, 2013) of how Psamtik I, king of Egypt, attempted to determine the original language of mankind. He ordered that two newborn babies be left in the care of a shepherd and that no one speak to them, hypothesising that their first word would be uttered in the root language of all people. When one of the babies cried *βεκός*, similar to the Phrygian word for "bread", Psamtik inferred that Phrygian was the oldest of all languages.

This anecdote provides us not only with an example of early scientific ingenuity, it also gives us a measure of what a daunting task it is to trace the origins of language. Scientists and philosophers have attempted to tackle this question from different and increasingly specialised perspectives. Rousseu, in the purely speculative *Essai sur l'origine des langues* (Rousseau, 2013), derived language from human's innate capacity for musical melody. Herder (2015) contributed to the foundations of comparative philology. Humboldt (1999) carried out in *On language* one of the first attempts at a systematic study of comparative linguistics, hinting at the joint development of language and mental powers. Language is the external appearance of a people's spirit ("die äußerliche Erscheinung des Geistes der Völker"), it is the embodiment of the collective imagination, culture, education and social practices of its speakers. Mental and social development cannot be understood without language development, and vice versa: the two are inextricably intertwined.

Recent times have seen many different lines of research contributing to tracing the origins and evolution of language. Of these, we can identify three broad categories that relate to the work presented here.

1. Some researchers try to identify *cognitive capacities* required for language. What cognitive skills allowed humans to develop a language when no other species could? How did these cognitive skills develop? Evolutionary psychologists and neuroscientists have focused on brain size evolution (Loritz, 1999), suggesting a co-evolutionary coupling between brain and language (Deacon, 1997).

   Tomasello's work tests and compares cognitive abilities of children and higher apes (see e.g. Tomasello and Brooks, 1999; Tomasello, 2003; Tomasello, 2014). What sets human beings apart, and what allows for the development of symbolic communication, is their unique capacity to cooperate.

   > Human communication is thus a fundamentally cooperative enterprise. (...) If we are to understand the ultimate origins of human communication, both phylogenetically and ontogentically, we must look outside of communication itself and into human cooperation more generally. It turns out that human cooperation is unique in the animal kingdom in many ways. (...) For reasons we do not know, at some point in human evolution individuals who could engage with one another collaboratively with joint intentions, joint attention, and cooperative motives were at an adaptive advantage. Cooperative communication then arose as a way of coordinating these collaborative activities more efficiently. (Tomasello, 2008, p. 6).

   The cognitive capacity to think in terms of *we*, to be able to engage in joint intentional activities, is a prerequisite for the emergence of language.

2. *Social and environmental conditions* which can explain emergence of language.

   Anthropologists and cultural paleontologists have investigated and suggested different possible social scenarios which might have contributed to the development of symbolic communication. A common thread running through virtually all of these theories is that an instinct for cooperative interaction, present in early human societies and young children but not in apes (Moll and Tomasello, 2007), is required for the emergence of language.

   Boyd and Richerson (2009) have suggested that the rapidly varying climates of the Middle and Upper Pleistocene may have caused the transition to altruism, favouring the natural selection of behaviours that enabled individuals to act collectively, learning from each other and coordinating their actions to reach a common goal.

   Bickerton and Szathmáry (2011), on the other hand, argue that climate changes in East Africa during the late Pliocene created drier and more variable conditions, giving rise to large areas of savanah. This caused a change in human behaviour, which transitioned from catchment scavenging to territory scavenging.

   > To access megafauna carcasses in the face of severe competition required that human ancestors communicate in ways no other primate had done, and cooperate to a degree unknown among other primates.

   Also, parties having to cover greater areas and butcher large carcasses while driving off competitive scavengers must have required much larger groups. The carcass finder had to communicate information that lay far outside of the sensory range and convince other group members to engage in an activity which potentially required a great expense of energy.

   Dunbar (1998) suggests that language emerged and evolved from gossip, as a form of social cohesion that substitutes grooming. Boyd and Mathew (2015) proposed a similar functional explanation of language evolution: symbolic communication might have developed as a way of ensuring that all members in the group cooperated and did not profit from the effort of the other members. Third party monitoring through language can help establish a reputation within a group, increasing the evolutionary fitness of those with a good reputation.

3. *Computer and mathematical modelling of emergence and evolution of language*. Researchers have employed agent-based computer simulations to study language as an adaptive complex system (Beckner et al., 2009; Steels, 1997c; Steels, 2000a; Gong et al., 2004). Language evolution can be understood as a dynamical system, a complex phenomenon emerging out of a multitude of simple interactions between agents. Evolutionary linguists have developed frameworks based on agents engaged in linguistic interactions to identify contributing elements in language evolution. Steels (1995) simulated the emergence and self-organisation of a shared lexicon in a group of agents without a centralised authority. Other authors (see e.g. Kirby, 1998; Hurford, 2000a; K. Smith et al., 2003) have investigated whether grammar-based languages can emerge as a result of the *poverty of the stimulus* for language learners. Language games have also been employed to simulate optimal evolution of grammar acquisition (Komarova, Niyogi, et al., 2001), communication costs (Čače and Bryson, 2007), or fitness benefits of language learning (Niyogi and Berwick, 1997).

1.2 LANGUAGE AND COOPERATION

Some time about 200,000 years ago one population of *Homo* began living in new ways which enabled it to spread out across the world, out-competing other populations and leaving descendants that are known today as *Homo sapiens*. The individuals of this species developed cognitive skills which allowed them to (Tomasello, 1999):

- produce a wide range of goal adapted stone tools;
- use symbols to communicate and to structure their social lives, including not only linguistic symbols but also artistic symbols such as stone carvings and cave paintings;
- engage in new kinds of social practices and organisations, with new forms of rituals such as ceremonial burials and other forms of religious, political and commercial institutions.

A common hypothesis is that cooperative communication began almost certainly in *mutualistic* collaborations: ones in which individuals cooperated only in order to obtain benefits to themselves (Hurford, 2007; Tomasello, 2008). Only later did individuals begin to share information and resources more freely, helping other individuals without obtaining a benefit, or even incurring a cost to themselves, in what is known as *altruism*.

1.2.1 *Coordinated behaviour*

The ability to coordinate collaborative activities more effectively provided individuals with an evolutionary advantage (E. A. Smith, 2010; Tomasello, 2008). E. A. Smith (2010) identifies several ways in which language helps in collective activities:

I. Language simplifies difficult coordination problems.

II. It reduces costs of monitoring and enforcing adherence to collective norms.

III. Symbolic communication enhances the broadcast efficiency of signals.

IV. Language facilitates positive assortment of individuals who adhere to similar norms and conventions.

Bratman (1992) enumerates several mental attitudes for shared cooperative activity, including meshing of sub-plans to carry out the joint action, as well as a commitment to help the other and a common belief in the activity.

Cooperation can potentially be rewarding, but it is definitely costly. Individuals must expend energy, abandon their own activity and spend time and effort coordinating the joint action. In adverse environmental conditions the cost of carrying out a cooperative activity may be very high, requiring lengthy travel or potential risks. Also, difficult activities require greater cognitive efforts to coordinate and to communicate effectively.

Language and cooperation are intertwined. Language would not have evolved without some kind of cooperation. On the other hand, an efficient language makes cooperation more effective. If we consider communication as a cost, then we can model the effects of this coupling between cooperation and language. Cooperating would contribute to making the language more effective, thus reducing the cost of communicating. At the same time, an increasingly effective language would gradually decrease the cost of cooperating, thus contributing to the fitness of cooperators, granting them a selective advantage. The more agents communicate, the more it is in their interest to cooperate, thus refining language more and more.

Cooperation can be seen as a long-term investment: individuals who are prepared to pay the cost of cooperating may develop a more refined tool with which to cooperate. Language would make cooperation cheaper, producing future savings which could provide cooperative individual with an edge.

However, if communication is too costly, then coordinating actions may prove to be too high an investment. Being too willing to cooperate would end up with neither cooperators nor knowledge.

1.3 IMPACT OF COOPERATIVE BEHAVIOUR ON THE EMERGENCE OF LANGUAGE

In this document I investigate and measure the impact of altruistic behaviour on the emergence and evolution of language within a group of agents engaged in language games. More specifically, I determine whether, and under what conditions, language could emerge in populations of altruistic and mutualistic agents. Also, whether a population made up of both types of agents could develop a common language, and whether the language itself would facilitate the predominance of one strategy over the other. Finally, I explore the effect of varying environmental and communication costs on the behaviour of the population and on the convergence to a common language.

To do this I have developed a language game in which agents decide whether to help other agents. The protocol of the game enables us to measure the effects of both costly actions and costly communications.

1.4 OUTLINE OF THE THESIS

The next two chapters provide a background review of the literature. Chapter 2 discusses recent research on mathematical and computational models of language evolution. Several models are presented in greater detail due to their proximity to the model used in this thesis. I describe models inspired by evolutionary biology, as well as models in which agents interact in an environment and models in which language transmission occurs from adults to children. The methodology employed in the research presented in this thesis makes use of elements from several of these fields. The main conceptual addition to common language game models is to transform the interaction into a sequence of costly decisions made by the agents. Agents must decide whether to engage in an interaction based on the costs of previous interactions.

Chapter 3 offers an overview of the literature on the evolution of cooperation. It traces a history of efforts by evolutionary scientists to identify the mechanisms that make the natural selection of altruistic behaviour possible. I present game theoretical models that test these mechanisms and determine the selective constraints they are subjected to. This is followed by a review of models of helping behaviour, as well as recent literature on the main subject of this thesis: the effect of different cooperation strategies on the emergence and evolution of language.

The next three chapters are the bulk of this thesis. Chapter 4 describes the methodology employed. I introduce the language game, describe its payoff function and its interaction protocol. I have performed four different experiments. They are designed to form a sequence of increasing linguistic complexity, the first two modelling a holistic language while the remaining two model a compositional language. Both sets of two experiments follow the same pattern. The first experiment investigates convergence to a common language in two separate groups of agents, one made up exclusively of altruistic agents while the other consists exclusively of mutualistic agents. In the second type of experiment, the population is mixed, so that altruistic and mutualistic agents interact with each other. The model features a revision protocol by which the agents can review their cooperation strategy to imitate more successful agents. In this case the results focus not only in language convergence, but also in whether one strategy dominates the other and spreads throughout the whole population.

Chapter 5 describes the first two experiments modelling a holistic language. I discuss the internal language of each agent, as well as their learning mechanism. I then present and discuss the results of each experiment. Results show that altruistic populations require fewer interactions to develop a common language as soon as environmental and linguistic costs increase above a limiting value with respect to the profit that agents can obtain from performing an action. A population of mutualistic agents does not develop a common language if the costs are above a given limit. Similarly, a mixed population of agents displaying both types of cooperation strategies will favour altruism if the costs are within limiting values. Above those, agents will favour mutualistic behaviour and the population will likely not develop a common language.

In the same way, chapter 6 presents the last two experiments, in which agents develop a compositional language. Agents have methods to produce and parse utterances, as well as induce a grammar from expressions they receive. Similarly to the experiments with holistic language in chapter 5, altruistic populations develop a more refined and extended compositional language than mutualistic populations as soon as environmental and linguistic costs increase above a certain set of values.

Finally, chapter 7 discusses overall results, contribution and future work.

2

MODELLING LANGUAGE EVOLUTION

In his *Theory of Harmony*, Schönberg (2003) argues that music rules were set down by pedagogues and theorists, painstakingly compiling the practices of the great composers into a system. Composers were too busy composing music to think about the rules they were creating. Scientific research follows a similar path. Excited by the possibilities offered by a relatively novel method, scientists research. At some later point they begin to categorise, classify and evaluate, taking stock of the progress made so far. In recent years research in language evolution has relied more and more on modelling as a way to hypothesise and test possible conditions of language emergence and evolution. Several authors have compiled reviews of the different models and methods employed (Vogt, 2009; Jäger et al., 2009; Nolfi and Mirolli, 2010; Grifoni et al., 2016). This chapter follows the lines established by them. It first discusses one of the main assumptions shared by most models, that language evolves as a complex adaptive system. Next follows on overview of the models, first by describing those based mainly on mathematical methods, then computational models. Finally, I present in greater detail several models that are closely connected with the methodology used in this thesis, before summarising the chapter.

2.1 LANGUAGE AS A COMPLEX ADAPTIVE SYSTEM

A crucial element of language is its social function. Language is used for human social interaction: its origins, development and structure depend on its role in human social life (Tomasello, 2008). Understanding how language has evolved in the human linage requires a holistic approach which includes investigating the combined effect of many interacting constraints, such as the structure of thought processes, perceptual biases, cognitive limitations and socio-pragmatic factors.

A Complex Adaptive System (CAS) arises from the interaction of many individual components as they adapt and learn from each other (Holland, 2006). The system uses its own experience as data, particularly the effect of those experiences on the system itself. A CAS identifies regularities in that experience and it compresses them in the form of a schema, competing with other rival schemata. The results of this schema are then fed back into the system, where they affect its standing with respect to rival schemata (Gell-Mann, 1994). In human societies, for example, a schema is a set of customs, traditions, myths; what Dawkins named a *meme*: a unit of cultural transmission (Dawkins, 1989). The interaction and competition between elements in the system affect the behaviour of the whole system while at the same time affecting the behaviour of the elements (Baicchi, 2015). We can list the following elements in language that identify it as a CAS (Beckner et al., 2009):

a. The system consists of multiple speakers interacting with each other.

b. The system is adaptive, i.e. speakers' behaviour is based on their past interactions, and current and past interactions feed forward into future behaviour.

c. A speaker's behaviour is the consequence of competing factors ranging from perceptual mechanics to social motivations.

d. The structures of language emerge from interrelated patterns of experience, social interactions, and cognitive processes.

Steels (2000a) identifies several mechanisms by which linguistic schemata emerge. Reinforcement learning (Sutton and Barto, 2017) which feeds back and reinforces linguistic elements that prove to be successful. A second element is self-organisation, a mechanism that arises when there is a positive feedback loop in an open nonlinear system (Kauffman, 1993; Nicolis and Prigogine, 1989). Elements that are successful propagate, which in turn makes them more successful. A third mechanism is structural coupling, where the success of one element facilitates the success of another element. Steels (1998) and Vogt (2005) carried out experiments to simulate the co-evolution of concepts and lexicon in which feedback from successful communicative acts led to the emergence of shared perceptual ontologies, which in turn aided in the development of a lexicon shared by all speakers in the population. Other experiments have modelled self-organisation of linguistic elements such as vocal sounds (De Boer, 1997), recursive grammars (Batali, 2002) or grammar (Steels, 2000b).

"Language is at the nexus of several complex adaptive systems: biological evolution, learning and culture" (K. Smith et al., 2003). Each of these three systems is constrained by evolutionary pressures which determine their adaptation, each of them operating on its own timescale. A language learner attempts to learn the language from its parents. Differences between the language of the parent and the child result in cultural evolution of the language itself. The language acquired by the learner contributes to the reproductive fitness of that individual. The use of language within a social context facilitates the learning of languages that most contribute to communicative success, pressuring for the selection of languages that are both learnable and expressive (Brighton and Kirby, 2001).

A holistic approach to language evolution must consider it neither as exclusively biological nor as exclusively cultural (Christiansen and Chater, 2008), but rather as a result of evolutionary constraints, as well as the interaction between them. Brain size is a biological constraint. The size of the brain determines 1. the number of dimensions that the brain can meaningfully distinguish; and 2. the number of possible interactions between these dimensions. Both contribute to the conceptual complexity that the brain is capable of, and thus the number of aspects of the world that individuals can communicate about successfully (Schoenemann, 2017). On the other hand, because humans are embedded to a high degree in social interactions which are vital to their survival, communicative success plays a central role in an individual's adaptive fitness and breeding success. Both processes co-evolved: language adapted to the human brain and the brain adapted to language (Deacon, 1997; Schoenemann, 2009).

2.2 MODELLING LANGUAGE EVOLUTION: AN OVERVIEW

2.2.1 *Analytical and agent-based models*

Vogt (2009) suggests three main types of models of language evolution. Each subsequent type offers greater possibilities of modelling in increasing detail:

1. **Analytical models**: commonly employ methods from the theory of dynamical systems to measure the frequency of a linguistic trait in a population, describing macro-evolutionary effects. This type of model is discussed in more detail in section 2.3.

2. **Agent-based analytical models**: assign a mathematical formula to each agent determining the learning mechanism of the agent. For example, Baxter et al. (2009), model usage of one of two grammars, α and β, by user i in a population of n language users with a variable x_i, which represents the fraction of time that user i employs grammar α (with $1 - x_i$ representing the fraction of time user i employs grammar β). At every time step two users, i and j, interact socially. User i and j produce n and m utterances respectively, totalling T utterances. Each user has a specified *receptiveness* λ, which can be described as the willingness to change her language depending on the grammar she hears from the other user. x_i changes according to the formula:

$$x_i(t+1) \propto \left(x_i(t) + \lambda \frac{n}{T} + \lambda H_{ij} \frac{m}{T}\right) \quad (1)$$

here H_{ij} specifies the relative weight that user i assigns to the utterances of user j, equivalent to the social status of j as perceived by i. λ and H_{ij} are weights assigned to the fraction of utterances produced by each user. Notice that this diffusion model is very similar to mathematical models of opinion spreading and other sociophysical models (Helbing, 2013). Similar models have been proposed to investigate how languages may become extinct when competing with other languages (Kandler, 2009; Abrams and Strogatz, 2003; Kandler and Steele, 2008). These models are based on a diffusion process affected by parameters like spatial dispersion or a language's low perceived status.

3. **Agent-based cognitive models**: in this type of model, agents are not specified by a mathematical formula but by a computational cognitive model. These types of cognitive models often contain mechanisms for parsing, creating and processing language, perceiving an environment, memorising language or the identity of other agents, etc. Section 2.4 analyses several examples of this type of model.

Distinguishing between these types is not straightforward: some models start by setting down equations and employ simulations to test their soundness; other models simulate evolution of linguistic aspects and use mathematical or physical methods to analyse the results. Agent based models allow the researcher a wider scope when it comes to analysing specific linguistic phenomena. While analytical based models offer great clarity and focus on establishing causal relations, agent based models can be finer grained and define more elements that could have a determinant effect on self-organisation processes.

2.2.2 *Transmission mechanism*

Another criterion by which we can classify models of language evolution is by the type of transmission mechanism it employs. Social psychologists have developed experimental methods to test hypotheses regarding the mechanisms responsible for the origin and persistence of cultural variation (Mesoudi, 2014). We can identify the following mechanisms:

1. **The transmission chain method**, or *vertical transmission* in the terminology of De Vylder and Tuyls (2006). This method is similar to the children's game "Chinese whispers". Originally developed by Bartlett (1932), it involves passing material along a chain of participants, the output of each participant becoming the input for the next. Many models of language evolution use this mechanism, most prominently the Iterated Learning Model (ILM) (see section 2.4.2). The links in the transmission chain are successive generations of language users. Generations can overlap, and reproductive fitness is determined by communicative success. Generations interact by adopting the roles of teacher and learner, or adult and child, although random interactions between individuals of the same generation are also possible, as is allowing the child to observe the interaction between two adults (Vogt, 2005). Language evolution models commonly investigate the emergence as well as the evolution of a language, which requires the first generation of language users to have no prior linguistic knowledge, though they may have an innate bias (Griffiths and Kalish, 2007; Thompson et al., 2016; Kirby et al., 2007).

   An important parameter in this type of model is the amount of data to which learners are exposed. By controlling the sparsity of utterances that children can observe, the researcher can determine the width of a linguistic *bottleneck* that constrains the learnability of a language (Brighton and Kirby, 2001; Kirby, 2002).

Biologically inspired models (see e.g. Nowak and Krakauer, 1999; Nowak, Plotkin, and Jansen, 2000; Komarova, Niyogi, et al., 2001; Komarova and Nowak, 2001) also employ this mechanism. It is an invaluable tool to examine the transmission from one generation to the next, and the evolutionary drift that results from such transmission. However, this tool imposes a structure in the population that determines their roles and how they are to behave. If one generation is a parent to the next, for instance, then the parents will teach their children, and it is their instinct to teach them well. Their behaviour is determined by their role in the population. This is a very interesting assumption if one is trying to study the effects of just such conditions. For instance, a researcher may wish to study the effect of prolonged parental care or neglect in the linguistic learning of their offspring, and how that may affect the form adopted by a common language. If greater care proves to be beneficial for the children's linguistic development, then that could be interpreted as a factor in explaining why individuals are prepared to dedicate so much care to their children. This is a form of altruism that has prolonged effects on the shaping of individuals and social products.
This type of conditioning, however, restricts the researcher who is interested in examining the difference between types of cooperation determined by the benefit obtained not by the recipient, but rather by the cooperator, which is a type of competition between social strategies which can have an effect on the emergence of language, and not only on its transmission.

2. **The replacement method**, *horizontal transmission* for De Vylder and Tuyls (2006). This method involves establishing a norm in a group of individuals and replacing them with new untrained participants. It is commonly applied in the *Naming Game* liter-

ature (Steels, 1997b; Steels, 1998; Steels, 2000b) (see below, section 2.4.1). These models often aim to study the self-organisation mechanism of linguistic adaptation. This requires an open system, where new elements can be constantly added by new members of the population.

Any new individual entering the population must go through a process of learning the rules of a language already shared, to a lower or greater degree, by the rest of the population. In this case, the evolution of the language and how it is shared by the population depends on the arrival of new members, rather than on the cooperative behaviour of already existing ones. This, of course, could be an extremely interesting problem to study, for agents may choose to cooperate only with members of the population who already know the language and are thus able to act together efficiently. The discrimination newly arrived individuals would have an effect on the language shared by the group, perhaps even to the point of forming *creole* or languages particular to sub-groups.

2.2.3 *Type of language*

2.2.3.1 *Holistic languages*

In a holistic language, complex semantic contents are expressed through utterances that have no internal morphological structure (Wray, 1998). The message conveyed by the utterance is not a function of internal parts, but rather of the utterance as a whole. The naming game is a good example of a holistic language. The meaning of the signal depends on the signal as a whole, and not on parts of the signal. It is the simplest type of language, making it very useful to model social or cultural aspects of language, or focus on emergence more than change. Models of evolution of holistic languages have used mainly two types of forms. Agents can store either:

1. A *dictionary* of meanings, which associates a word to one or several possible meanings and assigns a weight to each single association. This linguistic representation is open, it can be expanded by adding new items as required and either removing or decreasing the weights of existing associations. This form of language is used in naming game simulations, beginning with Steels (1995).

2. A *matrix* form language. In Hurford (1989), for example, individuals store *transmission* (figure 1) and *reception* (figure 2) matrices.

		Signals transmitted			
		w	x	y	z
Objects	a	$t_{1,1}$	$t_{1,2}$	$t_{1,3}$	$t_{1,4}$
causing	b	$t_{2,1}$	$t_{2,2}$	$t_{2,3}$	$t_{2,4}$
transmission	c	$t_{3,1}$	$t_{3,2}$	$t_{3,3}$	$t_{3,4}$

Figure 1: Hurford (1989). Language transmission matrix.

Here, each entry t_{ij} is the probability of giving signal j while attending to object i. The rows add up to 1.0.

		Objects associated with signal by receiver			
		a	b	c	d
Signals	w	$t_{1,1}$	$t_{1,2}$	$t_{1,3}$	$t_{1,4}$
received	x	$t_{2,1}$	$t_{2,2}$	$t_{2,3}$	$t_{2,4}$
	y	$t_{3,1}$	$t_{3,2}$	$t_{3,3}$	$t_{3,4}$
	z	$t_{4,1}$	$t_{4,2}$	$t_{4,3}$	$t_{4,4}$

Figure 2: Hurford (1989). Language reception matrix.

Here, each entry t_{ij} is the probability of having his attention drawn to j while receiving signal i. The rows add up to 1.0.

Several authors have developed interaction models in which agents also store two matrices, one used when acting as a speaker, or *active* matrix, and another when acting as listener, the *passive* matrix (see e.g. Nowak, Plotkin, and Krakauer, 1999; Trapa and Nowak, 2000; Komarova and Nowak, 2001) . An agent learns by updating the matrix that corresponds to the role it is performing in the interaction. Lenaerts et al. (2005) make use of a similar representation and include non-square matrices to investigate the evolution of synonyms and homonyms.

2.2.3.2 *Compositional languages*

Many models have focused on the evolution of particular linguistic traits, from very simple 'Noun-Verb' syntactic constructs (Nowak, Plotkin, and Jansen, 2000) to recursive grammars (Batali, 2002). A *Fluid Construction Grammar* (Steels, 2011) has also been employed to formalise an agent's language, (see e.g. Steels, 2004a; Spranger, Pauw, et al., 2012; Spranger and Steels, 2012; Beuls and Steels, 2013). Kirby (2000) uses a Probabilistic Attribute Grammar (PAG) (Stolcke, 1994), 'a context free grammar enriched with statistical information and a way of introducing attribute-value pairs as a semantic part of each rule' (Kirby, 2000).

Of course, there are models in which both types of language coexist in the same population, so that some meanings are expressed with a holistic signal while others are compositional (see below, section 2.4.2.1, as an example).

Compositional models need to determine a process by which agents induce or choose a grammar. Some mathematical models view the grammar as an element in a set of possible grammars (Komarova, Niyogi, et al., 2001). The interaction of the agents guides the whole or part of the population toward a specific grammar, which is then shared by all. Another approach is to determine cognitive processes by which agents interpret the utterances they hear and induce a series of linguistic rules that allows them to interpret and produce their own expressions. This latter approach lends itself better to modelling using cognitive agents. It is also more appropriate to investigate the relation between a population's language and the environment in which its members act.

2.3 MATHEMATICAL MODELS

A common analytical model is based on a differential equation stating the dynamics of the frequency of individuals who use a particular linguistic trait in a population of language users. This model assumes that communication has an effect on individual fitness. An individual using a commonly understood linguistic trait is likely to perform better, thus increasing reproductive fitness (Hashimoto and Ikegami, 1996; Nowak and Krakauer, 1999). The frequency of the linguistic trait is determined by the fitness of individuals who use it, compared to the fitness of individuals using other traits. Such models also include a probabilistic term that quantifies error in the transmission of language from one generation to the next. Nowak, Komarova, et al. (2001) use the following equation:

$$\dot{x}_i = \sum_{j=1}^{n} x_j f_j Q_{ji} - \phi x_i \quad i = 1, \ldots, n \tag{2}$$

where x_j is the frequency of individuals using trait j, f_j is the average fitness of those individuals; Q_{ij} is the probability that a child learning from a parent with linguistic trait j will end up using trait i; while $\phi = \sum_i x_i f_i$ is the average fitness of the population.

The next section presents an example of an analytic model of language dynamics.

2.3.1 *Dynamical model of grammar convergence*

Komarova, Niyogi, et al. (2001) develop a model to study the convergence to a common grammar in a population of language users. The model contains the following elements:

- A simple alphabet A of signals.
- A set Σ_1^* of all the possible strings which can be produced from A.
- A set Σ_2^* of all the possible meanings.
- A set of grammars, G.
- Each grammar G_i generates a subset of $\Sigma_1^* \times \Sigma_2^*$, a set of sentence-meaning pairs.
- Each grammar specifies a measure μ_i on $\Sigma_1^* \times \Sigma_2^*$ which represents how often each grammar may use a particular syntactic construct to refer to a meaning.
- A matrix, A, which relates grammars to each other. Each entry $a_{ij} = \mu_i(G_i \cap G_j)$ is the proportion of meaning-pairs that grammars G_i and G_j have in common. Hence a_{ij} is the probability that a user of G_i speaks an utterance that will be understood by a user of G_j.
- A matrix Q_{ij} accounts for errors in learning. It specifies the probability that a child learning from a speaker of G_i will learn G_j. This matrix depends on A since the latter defines how closely both grammars resemble each other.

Each individual in the population uses one grammar. The fraction of speakers who use grammar G_i is x_i. The fitness of an individual using grammar G_i is:

$$f_i = f_0 + \frac{1}{2}\sum_{j=1}^{n}(a_{ij} + a_{ji})x_j \qquad (3)$$

where f_0 is a background fitness, the same for all users.

In the case of a fully symmetric A, where $a_{ij} = a$ for all $i \neq j$ and $a_{ii} = 1$, all grammars are initially equally likely, since they all have the same distance from each other. In this case the fitness is:

$$f_i = (1 - a)x_i + a + f_0 \tag{4}$$

A parameter for *learning accuracy* q is the probability to learn grammar G_i given that the teacher uses G_i. Because all grammars are equidistant, the learner is equally likely to learn any G_j for $i \neq j$. Thus every entry in matrix Q is:

$$Q_{ii} = q, \quad Q_{ij} = \frac{1-q}{n-1}, i \neq j \tag{5}$$

Equation 2 becomes:

$$\dot{x}_j = (1-a)\left[-x_j^3 + x_j^2 q + \sum_{i \neq j} x_i^2 \left(\frac{1-q}{n-1} - x_j\right)\right] - \frac{(a+f_0)(1-q)(nx_j - 1)}{n-1} \tag{6}$$

This equation has three fixed points: 1. a fixed point in which all grammars are equally likely; 2. a fixed point in which one grammar, G_i, is the most used; and 3. a fixed point in which one grammar G_j is the least used. In the latter two cases, all other grammars have the same frequency.

Similar models have been proposed for lexical convergence (Komarova and Nowak, 2001) and simple syntactic rules (Nowak and Krakauer, 1999). The next section describes this last model in more detail.

2.3.2 *Conditions for emergence of syntactic communication*

Nowak and Krakauer (1999) employ common practices in evolutionary game theory to study how protolanguages can evolve in non-linguistic societies, as well as what conditions would make natural selection favour a language design based on syntax. The game is played by a group of individuals who can produce a number m of sounds. They transfer information to each other about n objects. Linguistic representation takes the form of a matrix P, the active matrix, where p_{ij} is the probability for a speaker that object i is associated with sound j. Matrix Q, the passive matrix, contains entries q_{ji} denoting the probability that sound j is associated with object i. In an interaction between two individuals, A and B, the speaker's language L is given by P and Q, whereas the listener has a language L', given by P' and Q'. When trying to convey information about an object i the speaker selects signal j with probability p_{ij}, and the listener infers object i with probability $\sum_{j=1}^{m} p_{ij}q'_{ji}$. The overall payoff for communication between A and B is then taken as the average of A's ability to convey information to B, and vice versa.

$$F(L, L') = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{m} (p_{ij}q'_{ji} + p'_{ij}q_{ji}) \tag{7}$$

If communication is successful both individuals see their fitness increase by F. In each round of the game every individual communicates with every other individual, and the rewards for each one are summed up. For the next round, individuals produce offspring proportional to their fitness. Children acquire language from their parents by sampling their response to each object.

Trapa and Nowak (2000) investigated the existence of a Nash equilibrium and an Evolutionary Stable Strategy (ESS) for this game. They determine that if P is a permutation matrix and Q is its transpose, then the language $L(P, Q)$ is a strict Nash equilibrium and an ESS.

This very simple mathematical model does not include learning through interaction. Nowak, Plotkin, and Jansen (2000) added this interactive learning to the model, together with other assumptions:

- A language contains n words.
- Individuals are born without any knowledge of words.
- In any new interaction only one word can be learned, i.e., agents are constrained cognitively.

- Words are memorised independently of each other, that is, agents do not learn dependencies between words.

The population dynamics x_i, i.e. the relative number of individuals that know the word W_i, is:

$$\dot{x}_i = R_i x_i (1 - x_i) - x_i \tag{8}$$

where $-x_i$ denotes a constant death rate. The rate constant $R_i = bq\phi_i$ is the average number of individuals who acquire the word W_i from an individual who knows it and:

- b the total number of word learning events per individual during a lifetime
- q is the probability of memorising a word after one encounter
- ϕ_i is the frequency of occurrence of the word W_i in spoken language

This kind of language can be considered non-syntactic: a word refers to an event. The model proposes a syntactic language used to refer to objects and actions, through nouns and verbs respectively, so that event E_{ij} is described by the sentence $N_i V_j$. The reproductive ratios are:

$$R(N_i) = \frac{b}{2} q_s \phi(N_i)$$
$$R(V_j) = \frac{b}{2} q_s \phi(V_j)$$

where $\phi(N_i)$ and $\phi(V_j)$ refer to the frequency of occurrence of noun N_i and verb V_j. The factor $b/2$ appears because either the noun or the verb are memorised in each interaction.

When does syntactic communication lead to a higher fitness than non-syntactic communication? Suppose there are n objects and m actions. Suppose further that a fraction p of the mn possible events occur, and that the other events do not occur. Then:

$$R(W_{ij}) = \frac{bq}{pmn} \tag{9}$$

we also have:

$$R(N_i) = \frac{bq_s}{2n}$$
$$R(V_j) = \frac{bq_s}{2m}$$

The fitness of syntactic communication exceeds that of non-syntactic communication provided:

$$\frac{(m^2 n + mn^2)}{m^2 + mn + n^2} \geq \frac{2q}{pq_s} \tag{10}$$

This inequality holds if the size of the system exceeds a critical value, that is, if the number of relevant events becomes large enough, in which case natural selection could favour a language design where messages could be formulated that were not learned before.

2.3.3 *Critical review*

Mathematical models are an extremely valuable tool to reproduce analyse phenomena. They provide researchers with the possibility of focusing on a small number of parameters and simulate the behaviour of the whole system depending on the values adopted by them. Observable effects are usually found on the macro-level, phenomena which can be measured within the whole group or society but which are the product of an accumulation of causes at the level of individual interaction. In order to do that, models must abstract away a number of elements which may prove invaluable in understanding the emergence and shaping of social products.

1. Models usually parameterise communicative success. The elements of a language are determined by how successful they are at providing satisfactory communication between agents. A model determines the communicative success of an element by assigning a probabilistic value to it and observing how the system behaves if this value changes. Further understanding may be gained by allowing the elements themselves to adapt depending on how successful they prove to be.

2. Mathematical models very often make no or very basic assumptions about the cognitive abilities of the interacting individuals. A linguistic token is either understood or it is not, an action is performed correctly or incorrectly, agents do not guess. Communication has many more grey areas, successful communication can be straightforward or immensely complicated. However, linguistic rules are determined by how agents are able to produce and understand utterances, as well as their understanding of the object that they are communicating about, the environment and the task at hand.

3. Linguistic elements are transmitted from one individual to another in a probabilistic way. There is also a probability that the social object is transformed during transmission, that it is not clearly interpreted or understood, or remembered wrong. As with other elements in mathematical models, these probabilities are assigned by the researcher as a further parameter. A more refined method is to allow the agents and their cognitive capacity determine how and what is transmitted. An individual may hear an expression from another individual and must determine what is meant by it. In order to do that it must reason within the confined limits of the interaction and learn and remember what was communicated and how.

4. Mathematical models introduce concepts such as fitness and payoff which provide another level of meaning to the process of selection. Linguistic elements are selected because they facilitate communicative success, and this success has a quantifiable effect on an individual's fitness.

It is important that models be kept as simple as possible if they are to enlighten rather than confuse phenomena. Models may remain simple, however, while still taking into account not only how the members of a group use the language, but also how they understand it and internalise it. Computational models allow the researcher to simulate the behaviour of the language within populations of agents that show limited by well defined cognitive affordances. It is the agents' linguistic and environmental capacities that determine what is produced, understood and transmitted.

2.4 COMPUTATIONAL MODELS

2.4.1 *Horizontal transmission: the* Naming Game

Wittgenstein (2001) introduced the concept of *language game* to ground language in the way it was employed by its users, studying "language and the activities with which it is entangled"[1] as a unit. An example of a simple language is as follows: the game is played by a builder and his assistant at work. There are four types of stones: blocks, pillars, slabs and beams. The builder calls out a word for the type of stone he needs, and the assistant fetches a stone. If the assistant brings the type of stone that the builder wanted, then we can say that the assistant knew what the word *meant*, and the language game was successful. This, Wittgenstein claimed, can be considered a "complete primitive language" (Wittgenstein, 2001, p. 13). Just as a move of a piece of chess can only be understood as part of the game in which the move is chosen, so the meaning of a word can be understood in the context of the language game in which it is used.

Steels (2005) adapted an extended the language game concept into a framework which has proved to be extremely useful in language evolution research. He proposed a method based on computer simulations of interactions between agents situated in an environment. Steels identified four elements that are required to achieve a minimal form of communication in a language game:

1 "Ich werde auch das Ganze, der Sprache und der Tätigkeiten, mit denen sie verwoben ist, das "Sprachspiel" nennen." (Wittgenstein, 2001, p. 16)

1. The agents need to be engaged in a cooperative task. This involves being situated in the same environment, which is the object of their interaction.

2. Agents need to have a medium in which signs can be constructed, i.e., a repertoire of sounds or gestures.

3. Agents can take turns.

4. Agents need to be able to share attention.

Steels (1995) investigated the emergence and evolution of lexica, ontologies (Steels, 1998) and grammar (Steels, 2000b). The simplest of language games, the *naming game*, was designed to analyse the self-organisation of a lexicon in a community of agents with no previous linguistic knowledge. Baronchelli, Felici, et al. (2006) describe the game in the following way:

The game consists of a set of agents situated in a controlled environment with a limited number of objects. Two agents are chosen randomly at each interaction; one is assigned the role of *speaker*, the other the role of *listener*. Their interaction is played out according to the following sequence of rules:

1. The speaker selects an object from the environment.

2. The speaker retrieves a word from its inventory associated with the object selected, or, if there is no such word, creates a new word.

3. The speaker speaks out the word.

4. The listener tries to identify the object by searching for that word in its inventory. If the word is included in the listener's inventory the it points to the object associated to that word.

5. If the listener identifies the correct object, then the interaction is successful. As a result, both players maintain in their inventories only the winning word, deleting all other words.

6. If the word is not included in the listener's inventory, then the game is considered a failure. As a result, the listener updates its inventory by adding an association between the new word and the object selected.

7. Every association between word and object is weighted with a score.

We can identify several key elements of the language game framework that contribute to non-centralised emergence and dynamism of linguistic features:

- **Random assignment of roles**: Every agent can be randomly assigned either role. An agent's language can always be altered if it plays the role of listener.

- **Invention**: The system is open-ended, new words can be introduced at any time, depending on whether the agent acting as speaker has previously learned a word for a specific object. If the language game is designed to replace agents by introducing new ones, then new words are effectively introduced at every stage of the game.

- **Alignment**: Agents align their languages after successful interactions. Different language game implementations have experimented with different alignment strategies, from erasing all other items in the inventory to updating the weights of connections between words and meanings through lateral inhibition (Steels and Loetzsch, 2012).

The naming game methodology has been employed in a large number of simulations investigating many aspects of language evolution. These include: encoding of lexical aspects through morphological markers (Gerasymova et al., 2012); emergence and evolution of markers for grammatical agreement (Beuls and Steels, 2013); evolution of case systems to mark event structure (Van Trijp, 2012) and evolution of grounded spatial language (Spranger, 2016). It has become a paradigm of computer simulation models of language forming and evolution. Languages form and are shaped through a process of self-organisation, responding to evolutionary, social and cognitive pressures. These pressures can be simulated and their effect observed. However, there has been so far little modelling of an individual's behaviours. Linguistic self-organisation responds only to communicative success, rather than any selection process that the agents themselves may be experiencing.

2.4.1.1 *Analysis of the Naming Game*

This simple protocol has been shown to converge to a unique lexicon shared by the entire population (De Vylder and Tuyls, 2006). Baronchelli, Felici, et al. (2006) show that the behaviour of the number of words stored in the system with respect to population size is governed by a power law distribution with exponent 3/2. This applies also to $N_w(t_{max})$, the time in which the maximum number of words is reached.

Agent based models often specify a system *topology* which sets up the connections between individuals and determines which agents can interact (Helbing, 2012). The behaviour of the naming game has been shown to depend strongly on the underlying topology (Baronchelli, Loreto, et al., 2006). A *mean-field* topology allows every agent to interact with all other agents. This was the case in the original naming game. Agents placed in a regular $d-$*dimensional lattice* can only interact with their $2d$ nearest neighbours. Baronchelli, Dall'Asta, et al. (2006) show that a topology of agents embedded in low-dimensional lattices is significantly less demanding on the agents, who have to memorise fewer words. Dall'Asta et al. (2006) compare the dynamics of the system when agents are embedded in several different *homogeneous* and *heterogeneous* networks.

2.4.2 *Vertical transmission: Iterated learning*

Pinker and Bloom (1990) claimed that features of grammar such as linear order, phrase structure or major lexical categories require an innate set of cognitive traits in humans, and must therefore be the result of evolutionary adaptation through biological natural selection. Kirby (1998) set out to prove through computer simulations how there may be other explanations for the emergence of syntactic features without recourse to natural selection, individual fitness or communicative success. The simulations addressed the *poverty of the stimulus* problem (Chomsky, 1980), i.e., grammar cannot be learned by children learning a language since they never have access to anything but a limited subset of possible linguistic production. K. Smith et al. (2003) claimed that it is precisely this scarcity which imposes evolutionary pressures on the language to develop structure, a pressure they name *bottleneck*. Similarly, Hurford (2002) employed simulations of grammar emergence and evolution to show that only generalisable languages become stable when learners are only presented with a subset of all the grammar contained in the agents' internal representations.

The ILM (Kirby, 1998; Kirby, 2001) is a language game modelling the transmission of linguistic behaviour over time. It is a transmission chain method, as described in section 2.2. ILM simulates transmission of linguistic behaviour through generations of agents, where the linguistic output of one generation serves as the input for the next. It is made up of four components:

1. *A meaning space*: a set of possible meanings. Kirby (1998), for instance, defines a meaning as a triple of attribute-value pairs. The three attributes are *Agent*, *Patient*, *Predicate*, whereas values can be of two classes: *Objects* or *Actions*. Other representations for meanings have been used: K. Smith et al. (2003) represent meanings as points in a multi-dimensional space, where each dimension has discrete values; Vogt (2005), as explained in more

detail later in section 2.4.2.1, encodes meaning as a point in an *n*-dimensional *conceptual space* (Gärdenfors, 2000). Vogt's experiment employs a 4-dimensional conceptual space, where each dimension corresponds to a perceptual quality: one for each red, green and blue component, and one for shape.

2. *A signal space*: a string of random characters with a bounded length.

3. *One or more learning agents*.

4. *One or more adult agents*.

A fixed number of games is played at each iteration. After each iteration a subset of the adult agents is taken out of the game and replaced by the same number of learners, while promoting an equally sized group of current learners to the status of adults. It is assumed that these new adults have learned enough of the language. Interactions always take place between an adult and a learner. As we see, the ILM involves a simplified model of population dynamics, as well as a *vertical* transmission of language..

Individuals have no initial linguistic knowledge, so that at the beginning of the game no agent is able to say anything. Therefore, as in the naming game, agents are assigned the capacity to invent new signals and pair them with a meaning. Different strategies for encoding and parsing signals have been explored, as have different linguistic representations, such as probabilistic attribute grammars (Kirby, 1998), definite-clause grammars (Kirby, 2001), compositional rules (Hurford, 2000b), or bidirectional graphs of nodes for meanings and signals (K. Smith et al., 2003). We will explore one of these methods in more detail below 2.4.2.1.

More recent research has focused on identifying the contribution of both biology and culture on the evolution of language (Kirby, 2017). An alternative approach to ILM makes explicit the contribution of the learner to the process of cultural evolution (Griffiths and Kalish, 2007).

Learning is modelled as hypothesis selection, where the learners combine the data obtained from observed utterances with a *prior inductive bias* which represents whatever biological constraints the individual is equipped with. In a Bayesian framework, learners select the most likely hypothesis by computing the probability of each, given their collected data and biological bias by means of the Bayes relation:

$$P(h|d) \propto P(d|h)P(h) \tag{11}$$

where $P(h|d)$ is the probability of hypothesis h given the data d; $P(d|h)$ is the likelihood that the data was produced by the hypothesis, and $P(h)$ is the prior probability of the hypothesis. As an example of applications of this extended model, simulations carried out by Thompson et al. (2016) show that cultural transmission can lead to linguistic universals without requiring a strong innate constraint: learners can learn a language universal even when their biological bias favours a different universal, and could easily acquire the non-majority type language given the appropriate data.

2.4.2.1 *Iterated learning in a language game: Talking Heads experiment*

Vogt (2005) presented a simulation of the emergence and induction of compositional structures in the language of a population of agents. A language is compositional if "the semantic values of complex representations are determined by the semantic values of their parts" (Vogt, 2005). In contrast to compositional structures, *holophrases* are holistic utterances whose semantic value is not determined by their parts, but rather convey a meaning as a whole. It is a common hypothesis that protolanguages were based on *holophrases* (Wray, 1998). The purpose of the simulation is to investigate how compositionality may arise from exploiting regularities found in holophrastic utterances (Wray, 1998). It does this by implementing and extending methodologies described above: it extends the *Talking Heads* experiment of Steels, Kaplan, et al. (2002), based on the language game methodology. Linguistic evolution is set within a population of agents who can learn from previous generations in an *iterated learning* process. It is worth considering these two elements in a bit more detail, since they represent some of the most significant research trends discussed thus far.

1. The *Talking Heads* experiment investigated the emergence and evolution of language by presenting an architecture that allowed cognitive agents to map perceptually acquired data to symbolic categories. An agent's conceptual repertoire is a co-evolutionary process simultaneous with the construction of its lexical system. The experiment consists of two robots equipped with a camera facing a white board displaying scenes that contain geometrical figures. Agents are capable of segmenting the image into objects. They can collect sensory data about each object, such as colour, position, size, shape, etc., which correspond to different sensory channels. A perceptual stream is thus a vector of all values of each of the sensory channels. At each interaction an agent is loaded into each of the robots, and they play a guessing game with the objects in the scene. The agent performing the role of speaker selects one of these objects, which then becomes the topic of the communicative interaction. If the other agent has no adequate category to discriminate this topic, then it will create a new category, which corresponds to a new set of features. Likewise, if the speaker does not have a symbol to express the category, it will create a new one. Thus, a shared lexicon and its underlying conceptual categories are shaped by the pressure of successful or unsuccessful communication. Both co-evolutionary processes are *selectionist*: categories and symbols will be discarded or refined depending on their success in communicative actions (Belpaeme et al., 1998).

2. The *iterated learning model* simulates linguistic evolution by iterating games over generations of a population that is divided into two groups: *adults* and *learners*. Adults have passed the

stage of learners and are assumed to have learned the language. At each iteration, learners master the language by interacting with adults. At the end of each iteration adults die off, and learners take the place of adults, being replaced by a new generation of learners.

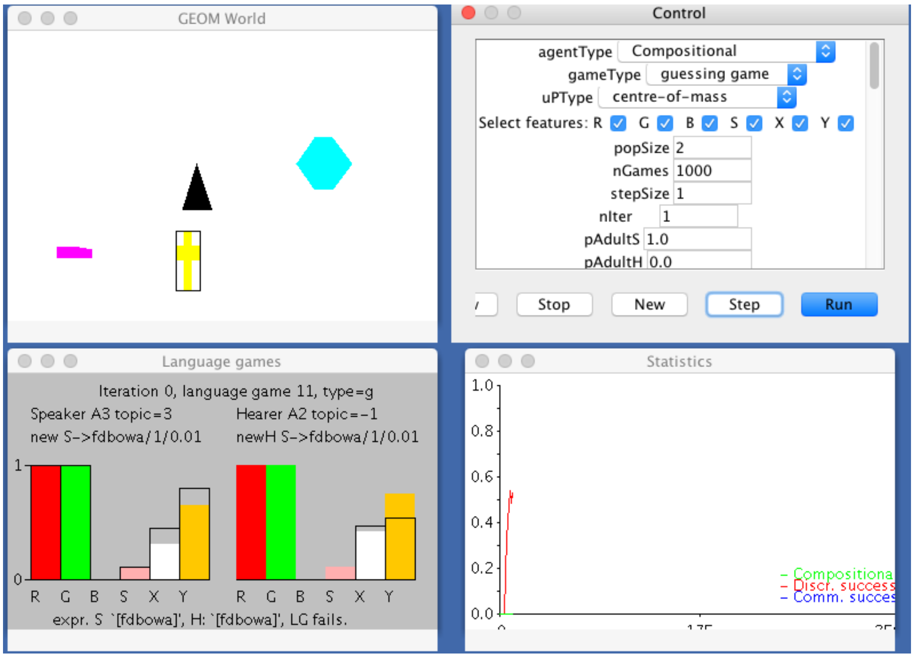


Figure 3: Vogt's *Talking Heads* experiment interface

Figure 3 shows the world as perceived by agents participating in the experiment. It consists of a scene made up of objects of 10 possible different shapes and 12 possible different colours. An agent has six possible different sensory channels: RGB values for colour, an S value for shape and X and Y values for the position of the object.

Each agent constructs its own private ontology by finding one or more categories for an object that distinguishes it from all other objects in the scene. Categories are represented by prototypes $c = (c_1, \ldots, c_n)$ which are points in an n-dimensional conceptual space. The points in the space that are closest to this prototype are defined as the category represented by this prototype. A conceptual space can be formed by combining the different possible sensory channels:

a colour space can be formed using all three values of the **rgb** features, or a 'redshape' space can combine the values of features **r** and **s**.

Each agent constructs its own probabilistic grammar starting from an initially empty set. The grammar is defined as a set of rules R, which might be either holistic or compositional. Some rules rewrite to compositional rules and others rewrite to single word utterances. Non-terminal rules can be combined with other rules through a composition operator. Each rule i has a weight s_i which indicates the effectiveness of the rule in previous interactions. The weight of a compositional sentence can be computed as the product of the weights of each of the rules employed in the composition. These weights are used to select among competing rules when encoding or decoding an expression.

Agents have several mechanisms to induce the grammar. Whenever the private grammar is not enough to communicate a meaning, be it because the speaker cannot produce an utterance or because the listener cannot interpret it, then the grammar must be expanded: the speaker may invent new knowledge and the listener may induce new knowledge.

- If the speaker cannot produce an utterance, then a new one has to be invented. Utterances are constructed from random letters taken from a subset of the English alphabet. The speaker has two ways of constructing a new utterance:
    1. The speaker may *exploit* an already existing compositional rule if it allows it to encode a part of the sentence. It does not create any new compositional rules, but can create a new rule that covers the part of the meaning that was missing, and associate to it a newly constructed word.
    2. The speaker can create a new *holistic rule*, and associate a new word with it.

- If the listener cannot interpret the utterance, then it has to induce its meaning. The listener constructs grammatical schemas based on similarities between utterances that it has heard in previous interactions. This type of learning is done through an *alignment-based learner* (Zaanen, 2003). The learner employs three different induction mechanisms:

  1. *Exploitation.* When a learner is able to decode only a part of the sentence, then it adds a new rule to cover the part remaining part.

  2. *Chunking* is used when an utterance-meaning pair is not parseable but a part of it aligns with stored utterance-meaning pairs. In this case, the learner will add a new rule for each of the chunks.

  3. *Incorporation* is done when no compositional structure can be induced, in which case the learner will add a new holistic rule to its grammar.

  In addition to these mechanisms, learners can also *generalise* and *merge*. Generalisation is a broader type of chunking: the learner will apply chunking to all rules that apply to a particular chunking step. Merging (Kirby, 2002) reduces redundancy in the grammar. There are two types of merging:

  – Rules with different non-terminal labels that are effectively the same are merged.

  – Rules that have the same non-terminal labels and the same word-forms but with different meanings covering the same conceptual space are merged.

Table 1 show an imaginary set of rules developed by an agent. S,A,B,C,D are syntactic categories, determined by which dimensions of the conceptual space they refer to. Utterances have been rendered in English to make them readable; in the model, however, they are made up of random characters.

R_1:	$S/\mathbf{rgbs} \to A/\mathbf{rgb} \quad B/\mathbf{s}$
R_2:	$S/\mathbf{rgbs} \to C/\mathbf{rb} \quad D/\mathbf{gs}$
R_3:	$S/\mathbf{rgbs} \to \text{redsquare}[1_{\mathbf{r}}, 0_{\mathbf{g}}, 0_{\mathbf{b}}, 1_{\mathbf{s}}]$
R_4:	$A/\mathbf{rgb} \to \text{yellow}$

Table 1: Grammar developed by agents in Vogt (2005)

The simulation keeps track of the evolution of the language measuring four different aspects:

1. *Compositionality*: the proportion of expressions that were encoded or decoded using compositional rules.
2. *Coherence*: the fraction of agents that produced the same utterance to name the same object.
3. *Accuracy*: the fraction of agents that could successfully interpret the utterances produced by other agents of the population.
4. *Similarity*: the average proportion of the grammar of adults that is acquired by learners at the end of each iteration.

Vogt provides a simple mechanism for the agents to develop their own grammatical rules, and to use those rules to produce utterances in their interactions with other agents. This mechanism also provides a simple way to decode expressions received from other individuals, by trying to match the expression received with one that the agent would produce using its own set of rules. The weights in the rules let the agent decide which rules to try to match first, in case there are several potential rules which could contribute in decoding the expression.

2.4.3 *Critical review*

The agents involved in computational models of language evolution act and interact in a vacuum. They are situated in an environment, they have objects that they point to and recognise and about which they communicate. But what is their motivation? Every model of language evolution assumes that agents are involved in cooperative interactions. As pointed out by Steels (2005), see above 2.4.1, agents interact in a shared environment and with shared intentions, they are communicating about the same task. But they have nothing to gain by communicating. Languages are shaped and transformed by their contribution to communicative success, but in what way does communicative success affect the individuals? Would communicative success always mean the same thing, or would a harsher environment, one where performing a task can be very costly, actually make a difference to the fitness of agents? A model of emergence of language would offer valuable insight if it were to include the following elements:

1. Agents communicate in order to perform an action which benefits both participants. Successful communication means that both can coordinate their actions and perform a joint task.

2. Performing a joint task is beneficial for both individuals. This means that the agents that perform the task are rewarded in terms that increase their fitness.

3. Performing the task is costly. There is a pressure on agents to perform in the environment. This pressure affects the agents' fitness levels.

4. Communicating is costly. In this way, the effect of not developing a common language can be expressed and measured.

5. Both costs contribute to the some of the agents' decision to communicate or not. Because performing the action is costly, agents are encouraged to cooperate whenever the benefit outweighs the cost. Because communication is costly, agents are pressured into behaving in a way that enables an efficient language to emerge.

6. Modelling the emergence of language in terms of cost and benefit allows the researcher to study the effect of evolutionary pressures on linguistic elements.

7. Linguistic elements are competing, in terms of being selected and preferred by agents. But agents, or rather, agents' behaviours are also competing, and the model can illuminate what effect each behaviour will have on the language, and under what conditions.

The next chapter will review several approaches to modelling behaviour in biological and social evolution. Focus on the evolution of cooperation will help to clarify how such models will be applied in this thesis to the study of how cooperative behaviours may influence the emergence of language.

2.5 SUMMARY

This chapter has provided an overview of models of language evolution. Most models view language as a complex adaptive system, evolving under biological, cultural and learning constraints. Language is constrained by human's cognitive capacity to learn, which in turn is affected by language. Individuals with greater cognitive capacities can develop more effective ways of communicating. At the same time, communicating effectively improves the reproductive fitness of those individuals, so that they are more likely to transmit their enhanced cognition and learning capability to future generations. Language and brain co-evolve.

I have discussed several classifications of language evolution models. A taxonomy suggested by Vogt (2009) classifies models according to their increasing detail, from population to individual language user. Analytical models propose a differential equation which governs the dynamics of a particular linguistic trait within the whole population. Agent-based analytical models set down a diffusion equation which define how an individual will acquire that trait. Agent-based cognitive models offer great variability in the way an agent acquires and processes language. A further distinction is made between the language transmission mechanism chosen by the model. The transmission chain model involves generations of language users who interact as teachers and learners. Language change is triggered by each generation of teachers dying out and the learners taking their place, while a new generation becomes the new learners. The replacement method sees individuals being replaced by new untrained participants one by one. The transmission is horizontal and a process of self-organisation takes place. A final distinction is established between holistic and compositional language models.

I analysed several mathematical models. These models are inspired by evolutionary biology and seek to establish the conditions which allow the language to stabilise around fixed points. Another model investigates the conditions that enable the emergence of syntactic communication. Through mathematical models the researcher is able to directly quantify the effect of varying parameters on the language viewed from a macro-level.

A section on computational models has reviewed the simplest possible model, the naming game. It has then presented some analysis carried out on simulations of the naming game. I have also discussed the ILM, first more generally and then in somewhat more detail by presenting an actual experiment. The Talking Heads Experiment (Vogt, 2005) models the emergence of holistic expressions, first, and then of compositional structures which the agents develop by applying simple grammar induction methods.

The language interactions that are investigated in this thesis occur between agents that display different types of cooperative behaviour. In the next chapter I discuss models of cooperation that can be found in the literature, the rational behind them and the focus each of them places on an aspect of helping behaviour.

3

MODELLING COOPERATION

3.1 COOPERATION IS A PUZZLE

The title of this section can be interpreted in two ways. Cooperation is a puzzle because its existence has perplexed evolutionary scientists working within the paradigm of natural selection of the fittest individuals. But it is also like a jigsaw puzzle: scientists have managed to gradually find new pieces which fit with other pieces to give an increasingly clearer picture, not only of cooperation, but of evolution also.

While writing *On the Origin of Species* in the late 1850s, Charles Darwin realised that honeybees posed a threat to the credibility of his theory of natural selection (Dugatkin, 2006). The problem was the existence of sterile castes in insects such as bees, wasps and ants.

> These workers are true altruists. In the first place, they do not reproduce but instead provide all sorts of resources to queens and the individuals who do reproduce. That alone would make them altruists, in the sense of incurring a personal cost that in turn benefits others. Some, but not all, sterile workers will also defend the hive tirelessly, if need be, with their own lives. (Dugatkin, 2006)

Natural selection is intrinsically selfish (J. L. Brown, 1983; Hamilton, 1964), favouring the evolution of traits that benefit solely and directly the *individual* who possess them. Traits such as sharp teeth, visual acuity or *crypsis* enhance an individual's chances of reproducing successfully, its *reproductive fitness*, thus increasing the probability that those traits will be inherited by future generations (Sachs et al., 2004). Darwin (1871) suggested that selection must operate at multiple levels. At one such levels, natural selection would operate on groups. A trait present in some of the members of a group that contributed to increasing the fitness of the whole group would provide it with an edge over competing groups and allow it to increase in number, spread and supplant other tribes. Natural selection would prefer a gene, rather than an individual (Dawkins, 1989).

Cooperation within a group is also perplexing, however. Individuals within the group which carry an altruistic gene would eventually disappear, since the probability of it being inherited by descendants decreases as does the reproductive fitness of altruists. Altruism would be recessive, and eventually the whole group would consist of non-altruists.

A further missing piece in the puzzle is the level of cooperation observed in humans. There are many instances of inter-specific cooperation in animals. Egg trading is a kind of mating behaviour in simultaneously hermaphroditic fish, in which individuals give up eggs to be fertilised in exchange for the opportunity to fertilise the eggs of a partner (Fischer, 1988). In other species of fish some individuals move away from the school in order to attract a predator's attention, thus reducing the risk of an attack on the school and increasing the risk of being attacked (Dugatkin and Mesterton-Gibbons, 1996). Many mammals such as lions or wolves hunt or protect territorial boundaries in groups. Apes groom each other and protect injured members of the group, as well as signalling predators at risk to themselves (Tomasello, 2009). Most non-human examples of cooperation take place within a close group of individuals, bonded by family relations and sharing a common pool of genes.

Homo sapiens is exceptional in that cooperation extends beyond close genealogical kin to include even total strangers on a much larger scale than other species (Bowles and Gintis, 2011). The evolution of cooperation at such level must have required the evolution of mechanisms that ensure the continued existence of cooperators, preventing cheaters and non-cooperators from dominating completely. The evolution of these mechanisms is likely to have had a profound impact on the evolution of human cognition (Tomasello, 2014), and it lies at the heart of human social and cultural institutions (Skyrms, 2004; Boyd and Richerson, 2009). It is a reasonable proposal that the unique aspects of human cognition were driven by social cooperation (Moll and Tomasello, 2007), from symbolic reasoning (Deacon, 1997), to moral values and emotions (Burton-Chellew et al., 2010; Boehm, 2012). The evolution of cooperation is one of the top 25 questions facing scientists today, according to the editors of *Science* (Kennedy and Norman, 2005), a clear sign of its scientific relevance.

Several reviews have been published in recent years that offer an overview of research on the evolution of cooperation (Redouan Bshary and Bronstein, 2004; Hammerstein, 2002; Lehmann and Keller, 2006; Fehr and Fischbacher, 2003; Sachs et al., 2004; West et al., 2007; Yamamoto and Tanaka, 2009). The next section offers a condensed summary of the very vast literature on the subject, focusing on what is most relevant to this document. This is followed by a discussion of game-theoretical models used by researchers to study the evolution of cooperation, including cooperative communication.

3.2 Evolution of cooperation

Cooperation is an act by one individual, A, paying a cost, c, for another individual, B, to receive a benefit, b (Nowak, 2006b). One initial distinction must then be made between two types of cooperation: in one type, *mutualism*, individual A pays a cost that benefits B, but A also benefits from the cooperation act. In the other type, A pays a cost but does not benefit from the cooperation. Mutualism fits a common pattern of selfish behaviour that increases the fitness of the individual (Bowles and Gintis, 2004); the fact that another individual also benefits is simply a by-product (De Jaegher and Hoyer, 2016; West et al., 2007). The second type, *altruism*, can only evolve within certain conditions. An altruism gene, G, is necessarily recessive, since any individual possessing that gene would see its reproductive fitness reduced, thereby reducing the probability of the gene being acquired by the next generation. Haldane (1932) suggested that the evolution of altruism can be explained if the behaviour of the individual resulted in an increment to the fitness of the group to which the individual belonged. This increment would be proportional to the frequency of altruistic members in the group. He also showed that there could be an initial increase of gene G provided the starting gene frequency was high enough and the cost low enough compared to the benefit to the group. Hamilton (1963) further showed that altruism could evolve in small groups which share common genes. Using Wright's *coefficient of relationship* r (Wright, 1922), he suggested that altruism would be selected if the gain to a relative of degree r is k-times the loss to the altruist, what is known as Hamilton's rule:

$$k > \frac{1}{r} \tag{12}$$

> Thus a gene causing altruistic behaviour towards brothers and sisters will be selected only if the behaviour and the circumstances are generally such that the gain is more than twice the loss; for half-brothers it must be more than four times the loss; and so on. To put the matter more vividly, an animal acting on this principle would sacrifice its life if it could thereby save more than two brothers, but not for less. (Hamilton, 1963, p. 355)

Hamilton's rule determines the condition for *kin selection* and expands the notion of fitness to include close relatives. Thus cooperation can be classified by whether it provides direct or indirect fitness (J. L. Brown and E. Brown, 1981; Grafen, 1984), with indirect fitness including the fitness of close relatives, ensuring the selection of the gene, rather than the individual.

This type of explanation is too restrictive, however, since we can observe altruism in non-related individuals or even between members of different species. Trivers (1971) proposed another mechanism for the evolution of altruistic behaviour: *reciprocal altruism*, also known as *direct reciprocity* (Nowak, 2006b). This mechanism relies on repeated cooperative interactions between both individuals:

> One human being saving another, who is not closely related and is about to drown, is an instance of altruism. Assume that the chance of the drowning man dying is one-half of no one leaps in to save him, but that the chance that his potential rescuer will drown if he leaps in to save him is much smaller (. . .). Were this an isolated event, it is clear that the rescuer should not bother to save the drowning man. But if the drowning man reciprocates at some future time, and if the survival chances are then exactly reversed, it will have been to the benefit of each participant to have risked his life for the other. (Trivers, 1971, p. 35)

Conditions for the evolution of direct reciprocity are quite restrictive. It is unclear whether natural selection will favour reciprocal altruism in sizeable groups. Several analyses suggest that reciprocal altruism can arise when pairs of individuals interact repeatedly (Borman and Levitt, 1980; Axelrod and Hamilton, 1981; Axelrod, 1984; Peck and Feldman, 1986; Boyd and Lorberbaum, 1987). Boyd and Richerson (1982) suggested that direct reciprocity would not be selected in groups larger than a handful of individuals because larger groups decrease the likelihood of two individuals interacting repeatedly. Also, individuals that do not cooperate but benefit from the actions of altruistic individuals would tend to see their reproductive fitness increased, so non-cooperative behaviour would end up being a dominant strategy. Evolution would be dependent on individuals following a contingent strategy called tit-for-tat (Axelrod and Hamilton, 1981): cooperate the first time you interact with another individual, but continue to cooperate only if the other individual also cooperates.

Cooperation can evolve in larger groups of unrelated individuals through a mechanism consisting of networks of individuals who are willing to help other individuals without expecting to be helped in return. Alexander (1987) imagines that individual *A* may help individual *B* although it receives no direct reciprocal benefit. However, *B* might help individual *C*, who then helps individual *D* who finally returns the help to *A*. In all these cases, contingent behaviour is based on local information: an individual knows what happen in the interactions in which it takes part, but does not know the behaviours along the chain (Boyd and Richerson, 1989). This mechanism is known as *indirect reciprocity*. Models have suggested that this type of mechanism is involved in the social status and reputation attributed to individuals in a group (Nowak and Sigmund, 2005; Martinez-Vaquero and Cuesta, 2013). Nowak and Sigmund (1998a) suggest that conveying the information required in this mechanism would have played a role in the development and evolutionary structure of language.

A third and final mechanism which allows the evolution of altruistic behaviour in large groups containing non-cooperators is known as *strong reciprocity* or altruistic punishment (Boyd, Gintis, et al., 2003; Bowles and Gintis, 2004; Bowles and Gintis, 2011). Many humans have a predisposition to punish those who do not reciprocate, even at a cost to themselves which reduces their fitness relative to other group members. Studies have found compelling evidence for such a mechanism from ethnographic studies of simple societies (Boehm, 1984) as well as from controlled laboratory experiments (Yamagishi, 1986; Fehr and Gächer, 2002). Several researchers Gintis et al. (2005), Boehm (2012), and Dugatkin (2006) have made the case that altruistic punishment lies at the core of the origins of moral values as well as sentiments like guilt and anger (Burton-Chellew et al., 2010).

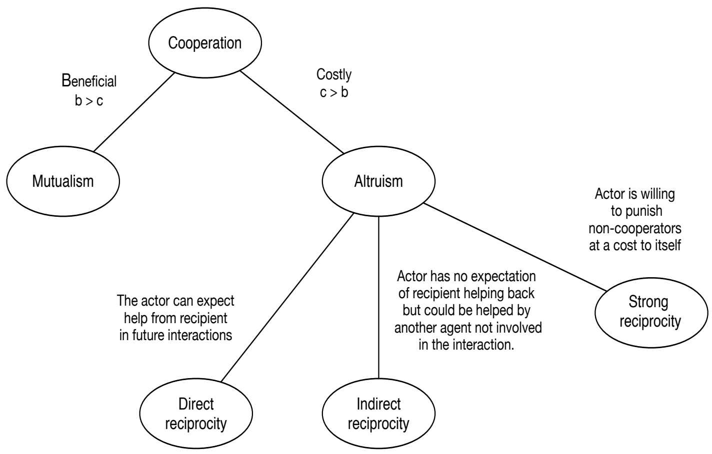


Figure 4: Types of cooperation. Cooperation takes different forms depending on whether the focal agent benefits from engaging. If the interaction is beneficial for the agent, i.e. if the benefit to the focal agent, b, is greater than the cost paid, c, then the cooperation is a case *mutualism*. If the cost is greater than the benefit, however, this is an *altruistic action*. In this case, a further distinction is made depending on whether the agent can expect reciprocity from the recipient agent in future interactions, *direct reciprocity*, or from another agent not involved in the interaction, *indirect reciprocity*. *Strong reciprocity* ensures cooperation when altruistic agents are willing to incur a cost to punish non-cooperators.

3.3 GAME THEORETICAL MODELS OF EVOLUTION

The theory of games was first formalised by Von Neumann and Morgenstern (2007) in reference to human economic behaviour. Game theory researchers set up and analyse highly abstract models of interacting agents and study the consequences of their possible actions. A central assumption of classical game theory is that players behave rationally, according to some criterion of self-interest. Players involved in an interaction may be anything, from bacteria to states that possess nuclear weapons: the concept of agent itself is an abstraction.

Game theory is only interested in the way actions chosen by an agent depend on the actions chosen by all other agents. Researchers have developed game models for a wide range of applications: firms competing for business, politicians competing for votes, road and network traffic, animals competing for mating rights, concepts of social justice, etc (Osborne, 2000).

Game models are highly varied depending on the phenomena under scrutiny, and include elements such as information available to the players, whether the game is repeated, whether both agents choose an action simultaneously or whether agents can learn from the interaction, thus affecting their strategy. There is, however, a basic set of elements that every game must have (Osborne and Rubinstein, 1994):

1. A set of players.
2. A set A of actions from which the players make a choice.
3. A set C of possible consequences of these actions.
4. A *consequence function* $g : A \to C$ that associates a consequence with each action. This is usually referred to as the *payoff*.
5. A *preference relation* $\preceq$ on the set C, known as a *utility function*.

A solution to a game is called a *Nash equilibrium*. It is a set of actions, one chosen by each player, such that no player would receive a better outcome by choosing a different action, given the actions chosen by all other players.

Modifying two of the elements of a game theoretical model makes it readily applicable to evolutionary biology (Maynard Smith, 1982). First, substituting rational utility by Darwinian fitness provides a natural way of measuring the impact of a biological trait or behaviour: an action will be selected that most increases the fitness of the individual. Second, the concept of solution can be substituted by that of an ESS. A strategy is a behavioural phenotype specifying what the individual will do in any given situation. An ESS is a strategy such that, if most of the members of a population adopt it, then no mutant strategy could invade that population (Maynard Smith and Price, 1973).

3.4 GAME-THEORETIC MODELLING OF COOPERATIVE BEHAVIOUR

Rousseau (1984) proposed a thought experiment in which every member of a hunting party must decide whether to cooperate with others and hunt a stag or abandon the party and settle for a hare, thus reducing the chances of his companions of hunting a stag:

> If it was a matter of hunting a deer, everyone well realised that he must remain faithful to his post; but if a hare happened to pass within reach of one of them, we cannot doubt that he would have gone off in pursuit of it without scruple, and, having seized his prey, cared very little, if by so doing he caused his companions to miss theirs. (Rousseau, 1984).

Scientists have used such thought experiments as representations of basic social situations. A formal representation of simple models like this can help acquire mathematical insight into social and evolutionary phenomena, such as cooperation (Skyrms, 2004). Figure 5 depicts the payoffs obtained by both players in a two-player stag hunt game.

		Player 2	
		Stag	Hare
Player 1	Stag	2,2	0,1
	Hare	1,0	1,1

Figure 5: Payoff matrix for the stag hunt game

This representation is known as a bi-matrix normal form game. Each row in the payoff matrix stands for an action available to player 1, whereas each column represents an action available to player 2. Each entry m_{ij} represents first the payoff to player 1 and then the payoff to player 2. We can assume that a player's preferences are ordered: every player prefers the highest possible payoff.

The *Prisoner's Dilemma* has been the model employed in a vast part of the research on the evolution of cooperation[1] (Rapoport et al., 1965; Trivers, 1971; Axelrod and Hamilton, 1981; Axelrod, 1984; Nowak and Sigmund, 1990; Nowak, 2006a; Cressman, 1992; Clements and Stephens, 1995; Mesterton-Gibbons and Dugatkin, 1997; Doebeli and Hauert, 2005; Raihani and R. Bshary, 2011).

Figure 6 shows the payoff matrix for the prisoner's dilemma. At each game, two players choose whether to cooperate (C) or defect (D).

		Player 2	
		C	D
Player 1	C	R=3,R=3	S=0,T=5
	D	T=5,S=0	P=1,P=1

Figure 6: Payoff matrix for the prisoner's dilemma game

Here R is the "reward" for mutual cooperation; P is the "punishment" for mutual defection; T is the "temptation" to defect; and S is the "sucker's" payoff. A prisoner's dilemma is defined by the payoff relation $T > R > P > S$, although most experiments have also investigated the relation $2R > S + T$ so that coordinated alternations between (C,D) and (D,C) outcomes are less profitable to the players than repeated (C,C) outcomes (Colman, 2003).

1 The name comes from an imagined scenario in which two prisoners find themselves under interrogation. Each prisoner has to choose between keeping quiet (cooperate) or betraying the other (defect). In this scenario, the payoffs shown in figure 6 are the sentence years.

Both players are tempted to defect, since the payoff for this action is the highest possible, if the other player cooperates. If the other player defects, then it is better to defect, since the payoff $P > S$. The Nash equilibrium is thus (D,D). However, if they both defect, then they both end up worse than if they had both cooperated. Hence the dilemma: both players are worse off by choosing the action that was most beneficial individually.

If the game is played more than once by the same players, then defection need not be a Nash equilibrium. We can assume that rational agents are likely to learn that in this case it is in their best interest to cooperate, and will assume that the other player has reached the same conclusion. Iterated games can test strategies that allow players to choose an action depending on what actions were chosen by other players in previous interactions, which action to choose when players meet for the first time and whether they can be sure that the current interaction is the last one, in which case they can try to profit from not being held to account in the future. Such strategies determine their long-term behaviour. Axelrod and Hamilton (1981) reported results from a competition of computer simulations of cooperation strategies using the prisoner's dilemma. The best results were obtained by a 'tit-for-tat' strategy, by which a player always starts by cooperating and thereafter imitates what the other player did in the previous interaction. Nowak, Sasaki, et al. (2004) showed that a single cooperator using a 'tit-for-tat' strategy would invade a population of defectors with a probability that corresponds to a net selective advantage.

3.4.1 *Modelling altruism*

There have been different approaches to model helping behaviour. One of the earliest models was proposed by Peck and Feldman (1986) who investigate the evolution of helping behaviour within a population in which two types of behaviour are possible. The two behaviours differ in the type and amount of 'goods' they produce and in the way they are distributed:

- Self-directed behaviour, S, produces goods that are received only by the performer of this behaviour.
- Group-directed behaviour, G, produces goods that are distributed evenly by both members of the pair.

Since fitness is determined by the relative values of the goods produced by each behaviour the authors set the value of goods produced by group-directed behaviour to 1 and vary the value, V, produced by S behaviour. The payoff matrix is presented in figure 7:

		Player 2	
		G	S
Player 1	G	1	$\frac{1}{2}$
	S	$1+\frac{1}{2}$	V

Figure 7: Peck and Feldman (1986). Helping behaviour payoff matrix.

Boyd and Richerson (1989) modelled the possible evolution of reciprocity by investigating the evolutionary stability of direct and indirect reciprocity in large groups. They study two possible scenarios which differ in the information available to the players:

1. In the first model individuals only know the other player's actions in previous shared interactions.
2. A second model allows for players to know whether the other player has consistently cooperated with other players in previous interactions.

Both models assume $b > c > 0$ always, and are represented by the same payoff matrix, depicted as figure 8:

A different approach is Nowak and Sigmund's model of helping (Nowak and Sigmund, 1998b; Nowak and Sigmund, 1998a). They in-

		Player 2 C	Player 2 D
Player 1	C	$b-c$	$-c$
	D	b	0

Figure 8: Boyd and Richerson (1989). Reciprocity matrix.

vestigate indirect reciprocity by modelling a situation in which players interact with each other with a negligible probability of ever encountering the same co-player again. The interaction is between a donor, who pays a cost c, and a recipient, who receives a benefit b. The simulation assumes $b > c > 0$ always. If the donor does not cooperate, they both receive 0. The payoff is shown in figure 9:

		Recipient
Donor	C	$-c, b$
	D	$0, 0$

Figure 9: Nowak and Sigmund (1998b). Indirect reciprocity payoff matrix

Each player has an image score s. Every time a player performs an altruistic act its score is increased by one unit. If it does not cooperate, the score is decreased by one unit. Potential donors decide to help depending on the image score of the recipient. A strategy is given by an integer k: a player with strategy k will provide help if the recipient's score is at least k. Donors that decide to help pay a cost, but they increase their score and are therefore more likely to receive help in the future. This model assumes that agents display cognitive capabilities which render them able to assign, recognise and remember such scores, a form of social tagging which can extend further than the immediate group.

These models rely on identifying mechanisms that make altruism possible, such as, for example, reciprocity or punishment. A different approach would be to pit altruistic behaviour against another type of cooperation with which it may even coexist, and test whether under certain conditions altruism would be selected. This can be done by simulating the dynamics under varying conditions of a population in which one or both traits are present. A trait that grants its possessor an advantage in terms of fitness is more likely to be selected.

3.4.2 *Evolutionary and population games*

Evolutionary games are a common tool to investigate evolutionary phenomena (Samuelson, 1997). Originally designed to study biological evolution (Hofbauer and Sigmund, 1998; Nowak and Sigmund, 2004), they have been widely applied in social and cultural evolution (Boyd and Richerson, 1988; McElreath and Boyd, 2007; Mesoudi, 2011) or socio-economics issues (Naldi et al., 2010).

An evolutionary game allows scientists to investigate the dynamic relations between two or more competing traits. It is commonly made up of two elements (Sandholm, 2010):

1. A *population game* describing the strategic interaction between the agents. It consists of:
    - A population of agents, P, who interact with each other.
    - A set of actions available to agents, $A = \{a_1, \ldots, a_m\}$. Actions are decisions made by the agents in their interactions.
    - A set of strategies, $S = \{s_1, \ldots, s_n\}$. A strategy determines which action to take during every possible interaction. Strategies may be *pure*, which determine actions uniquely, or *stochastic*, which define a probability distribution over possible actions.
    - A set of *population states*, $X = \{x \in \mathbb{R}; \sum_{i \in S} x_i = m_i\}$. The scalar $x_i \in \mathbb{R}_+$ represents mass of players in population p choosing strategy $i \in S$.

- A *payoff function* $F : X \rightarrow \mathbb{R}^n$ assigning a vector of payoffs to each social state. $F_i = X \rightarrow \mathbb{R}$ assigns a payoff to strategy $i \in S$.

Every interaction has an impact on the fitness of the participating agents, determined by the payoff function. An agent's fitness will thus be the sum total of the payoffs obtained in all its interactions, which will in turn depend on the distribution of each of the strategies across the population.

2. A *revision protocol*. The game specifies a procedure by which agents change or inherit a strategy. Some common procedures are (Taylor et al., 2004; Sandholm, 2012):

   - A *Moran process* (Moran, 1962): defines a procedure for a population with a fixed number of agents and overlapping generations. At every time step an individual is randomly chosen for reproduction, while another is randomly chosen for death, thus ensuring that the size of the population remains fixed. Natural selection is modelled by ensuring that the likelihood of selection depends on fitness: individuals with higher fitness are more likely to be selected for reproduction.
   - A *Fisher-Wright process* (Imhof and Nowak, 2006): is a procedure defined for a fixed number of individuals in non-overlapping generations. The distribution of each of the strategies at each generation depends on the frequency of each strategy at the previous generation.
   - An *imitation process*: defines a procedure for a population of fixed size. It does not require that individuals reproduce, thus allowing dynamicity in a population consisting of only one generation. This process is quite common in social and cultural evolution research (Helbing, 1992; Fudenberg and Imhof, 2008; Sandholm, 2012). One or several in-

dividuals are chosen randomly at regular intervals. These agents will be allowed to revise their strategy by comparing their own fitness to that of other randomly chosen agents. Whether the agents decide to imitate more successful individuals can be probabilistic or deterministic. An imitation protocol does not require new agents entering the population, and hence no new learning process. The evolution of a social product in a population with such a protocol can be monotonic, or at least any disruptions will not be caused by transmission between generations.

The revision protocol causes the frequency of each of the strategies to shift. The distribution over the frequencies can be unstable or it can eventually converge to a fixed equilibrium point. If the entire population converges to one of the strategies over the others then it is an ESS and we say that the population fixates to this strategy (Antal and Scheuring, 2006).

3.5 MODELLING COOPERATIVE COMMUNICATION

Research into the evolution of cooperative communication has centred mostly on the mechanisms that allow the evolutionary stability of honest communication. In competing environments individuals might gain an advantage by deceiving others (Desalles, 2000). Several models have been proposed to investigate the effect of cooperative and competitive behaviour in signalling games. Signalling games were proposed by Lewis (1969) to study the conventionality of meaning. A game consists of a sender, S, who possesses some information, t, about the world and wishes to share it with another player, the receiver, R (Skyrms, 2004). The sender chooses a signal, m, from a reduced number of potential messages and the receiver responds by choosing an action, a. The payoffs in the original game make it a cooperative game, with both players being rewarded if receiver interprets the signal correctly.

Noble (2000) has simulated the effect of competition and cooperation in the evolution of communication by modelling signalling games in which agents not only send honest signals, but can also cheat and signal the wrong information to other, and potentially rival, agents. Both players find themselves in an environment which is in one of two possible states, high or low. A high state indicates that the sender has found food, whereas the low state means there is no food present. The sender is aware of this state, and can signal this information. Signalling is costly, however, so senders decide whether to share the information with the receiver or not. The receiver can respond positively by performing an action, such as approaching the sender to share the food; or respond negatively, by not performing any action. Players receive a benefit only if the state of the environment is high. Figure 10 shows the payoff matrix for this game. Here b_R, c_R, c_S and c_R are the benefit and cost for the receiver and sender respectively. Noble shows that honest signalling is an ESS if:

$$b_S > c_S > 0$$

$$b_R > c_R > 0$$

		State of environment	
		Low	High
Signal	Neg. Response	0,0	0,0
	Pos. Response	$0, -c_R$	$b_S, b_R - c_R$
No Signal	Neg. Response	$-c_S, 0$	$-c_S, 0$
	Pos. Response	$-c_S, -c_R$	$b_S - c_S, b_R - c_R$

Figure 10: Noble (2000). Payoff matrix for cooperative signalling game.

Ackley and Littman (1994) proposed models in which the signal may be beneficial for receivers but the signallers are indifferent.

Oliphant (1996) applied reciprocal altruism to the evolution of successful communication. In his simulations, an agent could perform two types of communicative acts: a cooperative act and a retaliatory act, which would provide other agents with wrong information, as a form of punishment based on previous interactions.
While these models contain many aspects that are relevant to this document, such as the dependency on the state of the environment and the effect of communication on the players' fitness, it is somewhat limited in only considering honest against dishonest signals. Signals are a way of interacting with the environment, or denying other individuals the possibility of doing so, rather than with other agents. It also disregards learning: improving the signals does not make them more effective or contribute to the fitness of the players.

Wang and Steels (2008) explore a model called the Reciprocal Naming Game (RNG), a combination of the signalling game and the naming game, discussed in section 2.4.1. In this model agents can recognise each other, keep a record of cooperative behaviour and direct their altruistic behaviour towards those who previously offered cooperation. Payoff for both players depends on the action taken by R, $p = 1$ if the the message was interpreted correctly, otherwise $p = 0$. S can adopt a strategy of lying about t, in which case R adapts by ignoring information contained in m. As in the naming game, S selects one of two objects in the environment, only in this case one of the objects is the target, or the right object, while the other is used as a distraction. S selects the object according to its strategy, either providing correct or incorrect information. Each agent has a *social memory* in which they store a rating of each individual they encounter. Agents also have different strategies with respect to their lexical memory: short term memory deletes signal-meaning associations that fall below a threshold. Figure 11 shows the payoff matrix for the RNG, where each entry r_{ik} represents the payoff for S and R respectively.

	p=1	p=0
S cooperates	0.6,0.6	0,0
S defects	0,1	1,0

Figure 11: Wang and Steels (2008). Payoff matrix for the reciprocal naming game.

A measure of lexical agreement is *group coherence*, summarised by a group lexicon of the most popular words. Result show that retaliation allows deception to be tolerated. Because *R* guesses the meaning of a signal it does not know, agents can interpret this as defection, thus punishing agents who are actually cooperative. Therefore, lexical agreement depends not only on a complete lack of deception, but also on the ability to detect it. The game also shows that long term memory helps to achieve coherence. As was observed in Axelrod and Hamilton (1981), one mistake in an interaction can destroy confidence between players, hindering future cooperative interactions. Cooperative relationships become even more robust with long term memory. This research has many elements that are relevant to this document. Agents learn from other agents, and their language is affected by the other individuals' willingness to cooperate. Again, it investigates altruism by identifying a mechanism that makes it socially advantageous, rather than observing whether it can really compete against other forms of short-term beneficial cooperation.

3.6 EXTENDED GAMES AND DECISION TREES

All the game-theoretical models of cooperation reviewed in this chapter are in *normal form* (Shoham and Leyton-Brown, 2008). Interactions in normal form games are one-shot affairs: players choose an action simultaneously and receive the payoff. Which action they choose depends on their strategy, which in turn depends on an expectation of the strategy of the other player. Cooperative behaviour can be investigated if interactions are iterated; only then are mechanisms like punishment and fear of punishment significant. This is appropriate from an evolutionary point of view: an individual's reproductive fitness depends on that individual's complete history of interactions.

An alternative is the extensive form, where the player's decisions are a consequence of the other player's decisions within that same interaction. Games in extensive form are represented as trees, with each layer representing the decision of alternating players. The payoff for each player is determined after the interaction is over and is a function of the history of decisions made during the interaction.

Other game-theoretical model take into account the cost to player as a function of the effort invested. In the following two sections two such models are discussed.

3.6.1 *War of attrition*

Maynard Smith (1982) proposed the war of attrition, which models animal's display habits in confrontational interactions, whether competing for territories, resources or mates. Contestants display, and the winner is the one who displays the longest. Display is costly, which means that players cannot display for ever, if only because it delays the start of breeding. Moreover, the cost of displaying increases the longer it goes on. How long should a player display? Each player selects a cost that it is prepared to pay to obtain a value V. For players A and B the costs would be m_A and m_B. The winner would be the one selecting the higher cost. However, that would not be the cost to pay, since the length of the encounter is determined by the loser. The payoff matrix is:

	Player A	Player B
$m_A > m_B$	$V - m_b$	$-m_B$
$m_A = m_B$	$(V/2) - m_b$	$(V/2) - m_b$
$m_A < m_B$	$-m_A$	$V - m_A$

Table 2: Maynard Smith (1982). Payoff matrix for the *war of attrition*

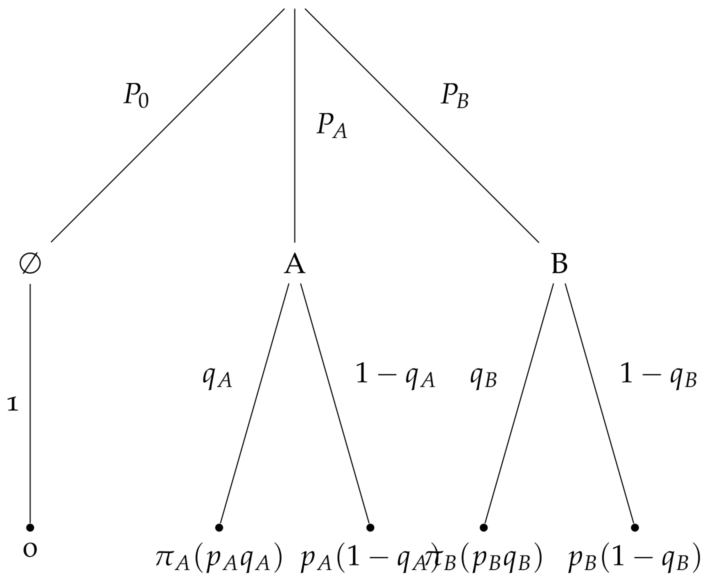


Figure 12: Cressman et al. (2014). Foraging decision tree model

3.6.2 *Decision tree models*

Cressman et al. (2014) proposed a model of the payoff received by a predator choosing a territory in which to forage, as shown in figure 12. The predator is hunting two different types of prey, A and B. At the top of the tree, it chooses a territory in which the probability of finding no preys is p_0, of finding a prey of type A is p_A, and of finding a prey of type B is p_B. If the predator finds a prey, then it must decide whether to attack it, which it does with probability p_A and p_B respectively, or not attack with probabilities $1 - p_A$ and $1 - q_B$. Attacking a prey carries costs π_A and π_B respectively. The payoffs to the predator are a function of all the probabilistic decisions made during the hunting, and of the cost of attacking. This is an example of a model in which the end cost of the foraging process depends on the decisions made throughout the process. Such a model can show the effect of learning if the forager directs its behaviour in ways that reduce the cost and thus increase the benefit of foraging.

3.7 A NOTE ON MODEL DESIGN

Normal form games such as those reviewed in this chapter are not the most appropriate if one wishes to investigate the effect of a behaviour on an emergent cultural product, such as language.

One way to model this would be to add a variable to the payoffs of a normal form game. This variable would function as a weight to the cost of cooperating. When the game is played iteratively, the variable would decrease as a function of the player's decisions, so that the more players cooperate the cheaper it becomes to cooperate.

Perhaps a more appropriate way to model the increasing efficiency of language, and decrease of its cost, would be to emulate the way language does indeed become more efficient: by using it. The effect of the communication cost could be contained in the interaction itself, so that the more that agents strive to *learn* a language, the more effectively they will be able to use it in the future. This is a way of modelling long-term strategy: being willing to pay more now in order to pay less in the future.

A game like this would look more like an extensive game. The payoff to the players would be a function of all the decisions made during the interaction and of their joint willingness to cooperate. Modelling helping behaviour would look somewhat like the decision tree in section 3.6.2. The payoff would be a function of the efforts of one individual to help another.

In the next chapter I present such a model, in which the helper decides during the interaction whether it wants to continue paying the cost of helping, and can defect at any point.

3.8 REGARDING SOCIAL LEARNING

Simon (1990) suggested a theory that accounts for altruism on the human tendency to learn from others, or to accept social influence, a tendency he calls docility. In his theory, altruism is not the product of natural selection, but rather the result of social learning, a process which contributes to an individual's fitness in two ways: first, it provides knowledge and skills that are useful in the individual's activities, particularly in transactions with the environment. Second, it allows the individual to acquire goals, values and behaviours which are supported by others.

Boyd and Richerson (1988) proposed a somewhat different mechanism, *conformist transmission*, which is preferential selection of behaviours individuals encounter more frequently. A behaviour that is already prevalent in a population is reinforced by those adopting it, because it offers greater support from other individuals who already display the trait.

Both mechanisms rely on a form of social learning based on imitation: individuals steer their behaviour in order to be accepted in the group. This trait itself is selected because the support offered by a large fraction of the population has a positive impact of the individual's fitness. Copying successful individuals is a common social learning mechanism, in human (Rendell et al., 2011; Schlag, 1998), as well as in animal societies (Horner et al., 2010), both in learning useful skills (Ottoni et al., 2005) and behaviours (Pike and Laland, 2010).

Whether cooperative behaviour is the product of genetic evolution or of social adaptation and learning is a question that is outside of the scope of the model presented in this thesis. The objective here is to test how the behaviour may affect the emergence of a cultural product, in this case language, and to determine conditions under which this emergence may happen. Cultural learning is more appropriate to the purpose of this model, because individuals do not need to learn the language from scratch, thus influencing its form and the elements that make it up. The model aims to isolate the effect of the cooperative behaviour, discarding other possible causes such as how reliably it can be transmitted or learned.

3.9 SUMMARY

This chapter has discussed recent efforts to understand the evolution of cooperative behaviour. Motivated by the assumption that cooperation has likely played a determinant role in the evolution of human cognition and social traits (Boyd and Richerson, 2009), researchers have attempted to model and simulate the evolutionary advantages of increasingly refined types of cooperation: working together for mutual benefit; altruistic behaviour which means that the agent must pay a cost for the benefit of another agent; and two forms of altruism, one in which the agent can expect to be directly reciprocated by the beneficiary, and another is which the agent may receive the help of another agent not involved in the interaction, or indirect reciprocity.

The chapter has also presented several models that simulate how cooperative behaviour offers agents an evolutionary advantage which may explain its selection. These models, inspired by the tools developed within the evolutionary game theory framework, simulate the effect of cooperative behaviour on the fitness of agents by computing the benefits obtained by the agent engaged in such behaviour against the costs incurred. A behaviour which increases the agent's fitness is a trait that offers an evolutionary advantage, thus increasing the likelihood of it being selected by transfer to future generations.

Different types of cooperation make increasing demands on the cognitive and cultural capacities of the agents involved. A game in which agents cooperate only if it is in their own interest requires only that the agent recognise that the reward is greater than the cost. Direct reciprocity, however, requires individuals capable of remembering previous interactions and who shun others who have shown unwillingness to cooperate in the past, because individuals who are willing to receive help but no help others (thus obtaining the benefit without paying the cost) would see their own fitness increased over those who display cooperative behaviour. Likewise, for indirect reciprocity to be advantageous individuals must be able to recognise social tags assigned to non-cooperative agents. Cooperation can evolve and become stable in a population if altruistic individuals are willing to punish non-cooperators, a strong enforcement of reciprocity. This suggests a process of co-evolution between cooperation and cognition (Tomasello, 2014), by which greater levels of cooperation have made increasing cognitive demands on individuals, which in turn has allowed cooperation to extend to larger groups or even outside of immediate groups.

The remaining chapters of this thesis explores the effect of different cooperative behaviours on the emergence of a particularly important social construct: language. As discussed in this and the previous chapter, several authors have employed game theoretical models to investigate the evolution of cooperation. Others have used them to research the evolution of language. None, however, have studied the interaction between the two; the next chapter will present the methodology by which I will attempt to fill this gap.

4

METHODOLOGY

In this chapter I present a model in which agents interact linguistically to carry out a joint action. Agents display two types of helping behaviour. They can be either *altruistic* or *mutualistic*. A mutualistic individual will help another if it can expect to obtain a benefit as a result. An altruist will help another individual even if it results in a fitness penalty to itself. An agent's fitness depends on its helping behaviour and on its ability to communicate effectively, an ability acquired by interacting with other agents. This model allows me to compare the effect of both types of behaviour on the emergence and evolution of a common language (Clements and Stephens, 1995; Mesterton-Gibbons and Dugatkin, 1997)

The following chapters report on four different multi-agent based computer simulation studies aimed at investigating the impact of both types of behaviour on increasingly complex populations and languages. The studies are of two different types. In the first type, agents interact exclusively with other agents who have the same strategy, in two different groups. In the second type, altruistic and mutualistic agents interact with each other. The population is mixed and both types of behaviour compete to dominate over the group. This chapter describes the design of both types. First, however, I introduce the game model, detailing the payoffs to both agents at each step of the interaction. It then discusses the agents themselves, their cognitive capabilities and the environment in which they interact.

4.1 GAME MODEL

Figure 13 shows the Coordinated Language Game model. It follows the progress of a communicative interaction between two agents. Agents assume two very different roles: one agent is the *speaker* and the other is the *listener*. These two roles are equivalent to the speaker-hearer roles in naming games (see section 2.4.1), adult-child in the ILM (2.4.2) or sender-receiver in signalling games (3.5). Roles are assigned randomly. During its lifetime, an agent ends up playing both roles approximately the same number of times.

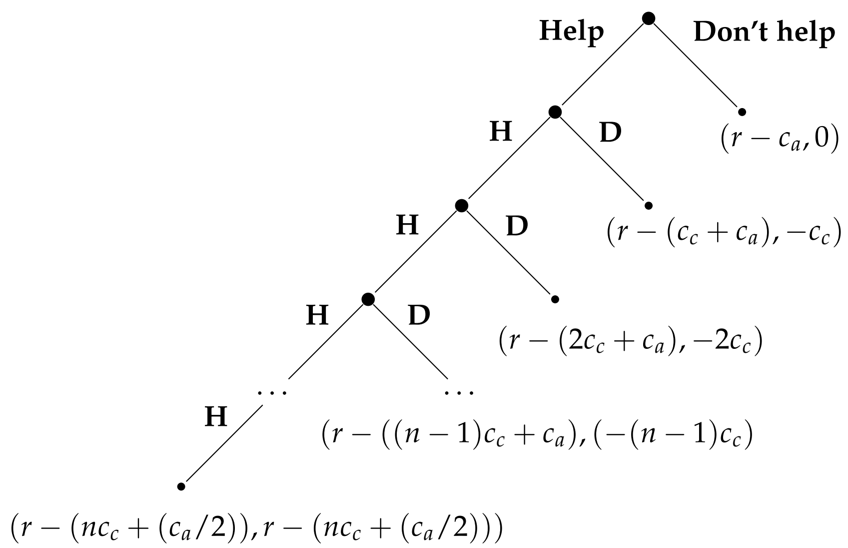


Figure 13: Decision tree representation of the coordination language game. Here r is the reward, c_a is the cost of carrying out the action, c_c is the coordination cost and n is the number of attempts the agents engage in. Each full node represents a decision point: the listener has a chance to evaluate whether to continue helping the speaker (H) or abandon the interaction (D or defect). A small node represents the end of the interaction, either because it is successful or because the listener has defected. Next to every end node is the payoff obtained by the speaker and listener respectively.

The tree traces the decisions made by the listener throughout the interaction. At the beginning, the listener encounters a speaker who wants to perform an action in the environment which could potentially be beneficial for both. Performing the action is rewarded with an amount r, but it requires paying a cost, the action cost c_a. If both agents act together they share the cost of carrying out the action. However, the agents need to communicate effectively to be able to coordinate their efforts successfully. Coordinating their efforts is time consuming, squandering valuable time which could be employed in other activities. It also requires cognitive effort and a certain level of trust on the other player. Coordinating efforts is thus costly, and the cost depends on how well they can communicate. Being able to communicate effectively can therefore provide a significant advantage to players who can act together quickly. This cost is called the coordination cost, c_c.

The interaction proceeds as follows:

1. At the root of the tree, the listener decides whether to help (H) the speaker or to defect (D). Its decision is based on the experience gained in previous interactions. If it decides not to help, the speaker performs the action alone, paying the full action cost, but also receiving the full reward. The listener pays nothing and receives nothing. The payoffs are $(r - c_a, 0)$, where the first entry is the speaker's payoff and the second the listener's.

2. If the listener decides to help, they engage in a linguistic interaction which follows the usual protocol of language games discussed in section 2.4.1. The speaker produces an utterance that refers to the action. It may be learned or invented, depending on whether the speaker has acquired it in previous interactions. If the listener understands, or guesses, the action correctly, they perform it together and receive as payoff the reward minus the coordination costs and half the action cost, $(r - (c_c + (c_a/2)), r - (c_c + (c_a/2)))$.

3. If the listener does not identify the right action, however, it must decide whether it wants to continue helping. Defection means that the speaker must perform the action alone, paying the full action cost and the coordination cost incurred. The listener must only pay the cost for failing to communicate. Payoffs are $(r - (c_c + c_a), -c_c)$.

4. The listener may decide to continue trying to help, in which case it makes another attempt at interpreting the action correctly.

5. After each attempt, the listener has the choice of defecting. If it does at any point in the interaction without having chosen the right action, both agents pay the cost of however many times they have tried, $-nc_c$, where n is the number of failed attempts. Defecting at any time during the interaction has payoffs $(r - (nc_c + c_a), -nc_c)$.

6. If the agents are able to complete the task and perform the action successfully they both receive the reward. The benefit to them is then the reward minus half the total cost. The total cost is half the action cost and the coordination cost for the failed attempts. Payoffs after a successful interaction are $(r - (nc_c + (c_a/2)), (r - (nc_c + (c_a/2))))$.

4.1.1 *Altruism and mutualism*

The game is played by two types of agents, altruistic and mutualistic. Whereas an altruistic listener always helps, a mutualistic one decides whether to engage in, and continue with, the interaction by calculating the benefit it can expect to obtain from it. It does not know the exact cost, since it cannot predict how long it will take to understand the speaker, but it can compute an expected cost using the costs of previous interactions. The probability of cooperating p is:

$$p = \frac{r - (c_e) + nc_c}{r} \tag{13}$$

where c_e is the expected cost and n is the number of guesses already attempted. Notice how the agent includes the coordination cost already incurred in the current interaction. The first decision is not affected by this cost, since $n = 0$. But as the interaction progresses, the probability of defection increases.

The mutualistic agent computes the expected cost, c_e, by averaging over the cost it paid in the previous k interactions.

$$c_e = \frac{1}{k} \sum_{i}^{k} c_a + n_{t-i} c_c \tag{14}$$

where t is the current interaction and n_{t-i} is the number of attempts at interaction $t - i$. Here k can be thought of as an agent's self-interest memory window. In the studies reported in this thesis, this window is always 1, i.e. agents remember only their last interaction.

4.2 SIMULATION ELEMENTS

4.2.1 *Agents*

An agent has perceptual, strategic and cognitive knowledge.

- It can distinguish colours, shapes and directions. It can discriminate objects based on these attributes.
- It is able to recognise all the possible actions that can be carried out in the environment.
- It knows the value of the reward and can remember the cost of the last interaction.

4.2.1.1 *Agent's language*

An agent has a semantic space: a set of meanings about which agents communicate. The meanings are made up of three semantic categories: *shape*, *colour* and *direction*. A meaning is a triplet of attribute-value pairs, one attribute each for *shape*, *colour* and *direction*. A meaning corresponds to an action. Each attribute can be paired with two possible values: *shape* can be either **ball** or **box**; *colour* either **green** or **red**; and *direction* can be either **right** or **left**. There are eight possible meanings, which correspond to the eight possible actions offered by the environment.

They also have an alphabet of symbols, Σ, which they use to produce utterances. Agents have no initial linguistic knowledge, i.e. they have no mappings between symbols and meanings.

The way agents learn language varies slightly depending on the type of language. This will be discussed in further chapters. Common to all studies is that only the listener learns, not the speaker. Agents only learn from positive feedback; that is, they only store or reinforce a connection between symbols and meanings when they have identified the action correctly.

4.2.2 *Environment*

Agents interact in an environment which consists of three cells. In the middle cell, where they meet, are four objects: a red box, a red ball, a green box and a green ball. These four objects are present at every interaction. Binary values for all semantic categories ensures that agents can only identify objects and direction through language. The environment allows a set of actions, A, of size eight. The speaker knows which action $a_i \in A$ must be performed while the listener does not. This is similar to a signalling game, as discussed in section 3.5. The action is always to move one of the objects to one of the neighbouring cells. The meaning of the action always contains all three category meanings, and these three are enough to identify the action. I therefore dispense with the use of verbs. In what follows I assume that the triple of attribute values **red ball left** is equivalent to the action 'Move the red ball left'.

4.2.3 *Interaction protocol*

Agents interact in a way similar to the *guessing game* (Steels, Kaplan, et al., 2002; Steels, 2004b; Vogt, 2015). Two agents are chosen randomly from a population, and are assigned roles also randomly. The speaker knows which action is to be performed. It searches its internal language and looks for a symbol or set of symbols associated to the meanings contained in the action. If it finds one, it uses it to produce an utterance. If it does not, then it produces one randomly. A cooperative listener tries to identify the action by decoding the utterance searching its own internal language for an association between the utterance and the meanings associated to an action. A successful interaction means that the listener has identified the action correctly. After every unsuccessful attempt, the listener has the choice to try again or defect.

4.3 parameter space

The studies investigate the behaviour of populations of agents who cooperate under the pressure of two costs: the action cost, c_a, and the coordination cost, c_c. Our studies measure whether, and under what conditions, two different types of cooperative behaviour affect the evolution of language. I therefore run simulations of the development of language under increasing costs.

The strategy is simple. Costs are sampled at discrete intervals from a range of increasing costs. The range of values of c_a is $(0.01r, 1.15r)$, whereas the range of c_c is $(0.1c_a, 1.15c_a)$. Parameters are fixed at each possible combination of these values and a batch of simulations is carried out under each value pair. Every simulation was run at least 20 times, to ensure that the measures extracted could be tested for normality (Lindsey, 2004).

4.3.1 *Measures*

To keep track of language convergence I employ *consistency* (Gong et al., 2004), a pragmatic measure of similarity between two languages. Intuitively, consistency measures the likelihood that any randomly chosen pair of agents would communicate accurately, regardless of the roles assigned to each agent. Accurate communication requires that two conditions are met:

1. Both agents interpret each other's utterances correctly, i.e. they identify the right action.
2. Both agents encode and decode the utterances uniquely. If the agent's internal language produces a set of candidate utterances that can express one meaning, the weights associated to the mechanisms that produce the utterances must have a unique maximum value. The agent would not have to choose randomly between several equally likely utterances. Conversely, the set of weights associated to all candidate mechanisms that decode an utterance must have a unique maximum value. Agents would not have to choose randomly between two equally likely interpretations.

The consistency is averaged over all possible encodings, i.e., the total number of actions that could be expressed given the environment.

$$C = C/|A| \tag{15}$$

where

$$C = \sum_{a \in A} S^a_{ij} / \binom{N}{2} \tag{16}$$

is the number of pairs of agents that communicate an action accurately out of all the possible pairs of agents. Here $|A|$ is the cardinality of the set of actions A, S^a_{ij} is a pair of agents, i and j, that can communicate action $a \in A$ accurately, and N is the population size.

I propose a measure of similarity for the compositional languages developed in the experiments reported below, chapter 6. This measure, *compositional spread*, requires a firmer grasp on how agents develop their compositional grammars during interactions, so a detailed discussion of this measure is better left until such time. I explain compositional spread in section 6.2.2.

4.4 DESIGN OF STUDIES

The studies were designed to verify the effects of altruistic and mutualistic behaviours on different stages of language evolution. The main design concept was to allow a smooth transition from one stage to the next, without jumps that would introduce extraneous parameters.

4.4.1 *Type I study: independent populations*

The Type I study sets up two independent populations of purely altruistic and mutualistic agents respectively. Agents interact only with other agents of the same type. Here, the cooperation strategies do not compete with each other. In this type of study I can observe and compare the effects of both types of cooperation in isolation. The effect on the language of each population can only be attributed to the behaviour of that group, not to the interaction between both types of cooperation. In the first study, for example, we measure the speed at which language converges in both populations. Because both behaviours act independently, we can safely assume that any differences in the speeds can only be attributed to the behaviour.

This type of study involves formulating a hypothesis about possible differences in the evolution of the languages of both populations, and testing the hypothesis from samples extracted from both groups.

4.4.2 *Type II study: mixed population*

In Type II studies, altruistic and mutualistic agents interact in one single mixed population. This type of study allows us to study the competition between both behavioural traits.

Both behaviours compete for selection in the population. The behaviour determines the reproductive fitness of the individual. In an evolutionary process, the behaviour that provides the individual with a fitness advantage enjoys a greater probability of being passed on to future generations. In the absence of further competing behaviours or other evolutionary pressures, it will eventually spread throughout the whole population and will be evolutionary stable. In this set of studies I wish to avoid introducing new generations of language learners to simplify the parameter space as much as possible. New language users would have disruptive consequences in the trajectory of the language which lie outside the scope of this document. It is possible, however, to emulate reproductive selection by means of a revision protocol. As described in section 3.4.2, a revision protocol is a mechanism that allows individuals to change their behaviour. The probability of agents adapting a new behaviour is proportional to the difference in the average fitness of both behaviours (Sandholm, 2010). The revision protocol adopted here is a simple deterministic imitative process. Several individuals from the population are chosen randomly. They take on the role of *imitators*. An equal number of indivuals is chosen, also randomly, to act as *role-models*. Every imitator compares its own fitness to that of a role-model and changes its behaviour if its own fitness is smaller.

This study introduces a further parameter, an initial number of altruistic agents. My aim is to test whether a very small number of altruists will be capable of dominating the entire population. Because the fitness of an altruist depends not only on its own behaviour but also on the behaviour of those it interacts with, I investigate what is the minimum initial number of agents required to dominate the population. Also, I wish to determine whether this initial number has an impact on the evolution of language.

4.5 SUMMARY

This chapter has introduced the game-theoretical model employed in the four simulation studies that will be discussed in the next chapters. The model consists of a set of payoffs for each player at every possible exit from the game. The game consists of a series of decisions made by the listener, who must decide whether to help the speaker to carry out an action. Performing the action might be beneficial for the listener also, in which case helping is not altruism but rather mutualistic behaviour. By varying the conditions that determine these payoffs I can compare the performance of each behaviour in the population. The model also allows us to estimate the effect of both types of behaviour on the evolution of language: succesful communication, and thus learning, depends on the cost that agents are willing to pay to help other agents.

I have defined altruism as an individual's willingness to cooperate regardless of the cost to itself. Mutualistic behaviour is motivated by self-interest: agents will help another agent if they expect to benefit from it.

The text then goes on to describe the elements of the model: the agents, their cognitive capabilities and the enviroment they interact in.

I have then summarised the language game and its protocol, the measures used to follow the evolution of the language and the model's parameter space. This space is made up of two costs, an action and a coordination cost.

Consistency is a measure of the likelihood that a random pair of agents can communicate accurately.

Finally, the chapter included a description of Type I and II studies. Type I sets up two populations of agents, one altruistic, the other mutualistic. From these two groups I can sample measures and test hypotheses. Type II has altruistic and mutualistic agents interacting in a mixed population. The study features a revision protocol, which allows us to observe the system's dynamics and eventual fixation.

5 FIRST CASE: EMERGENCE OF HOLISTIC LANGUAGE

In this chapter I report on two studies that investigate the effect of altruistic and mutualistic behaviours on the emergence of a holistic language. A holistic language associates a single utterance, a *holophrase*, with a meaning (Wray, 1998; Wray, 2000).

The purpose of the first study is to simulate the dynamics of language emergence in two separate groups. As described in section 4.4.1, one group consists entirely of altruistic agents, the other of mutualistic agents. In this idealised scenario, I am interested in examining whether both groups converge to a common language, and how fast they do so. The reasoning is that, even if altruistic agents have to pay a greater cost, their willingness to help other agents will eventually lead to long-term fitness gains by developing a shared lexicon, thus reducing the cost of communicating.

My hypothesis in this first test is as follows:

> Altruistic behaviour has a positive effect on the convergence to a common language within a population of agents engaged in a language game. A group of altruistic agents will converge to a common language faster than a similar population of agents displaying mutualistic behaviour.

The second study is aimed at verifying whether altruistic behaviour does indeed lead to a fitness advantage in a population in which altruistic agents interact with mutualistic agents. The simple revision protocol described in section 4.4.2 ensures that whichever strategy provides greater fitness benefits to the individual will end up spreading throughout the entire population. I am interested in determining whether such a population can develop a common language.

I begin by describing the agents' language and their language learning process. I then present and discuss the results of each of the studies.

5.1 LANGUAGE LEARNING

5.1.1 *Language matrix*

A population P consists of n agents. The agents are situated in the environment described in section 4.2.2. Agents communicate about actions that they perform jointly. There are eight possible actions in the environment. The set of actions, A, is thus of size eight. Because I am interested in the effect of cooperation on the convergence to a common language, our model reduces the language to a minimum. I therefore assume that all agents are capable of producing and perceiving the same eight different symbols[1]. More or fewer symbols would likely lead to synonymy and polysemy respectively, an unnecessary complication. Every agent has therefore a set of symbols, S, of size eight.

An agent's language consists of a series of associations of symbols and actions. Every agent stores a 8×8 matrix, L, like the one shown in figure 14. This is similar to linguistic representations discussed in section 2.2.3.1.

Every entry $l_{i,j}$ in L is the probability that word s_i is associated with action a_j. For every action, a player holds a distribution over all symbols $s \in S$, that is:

$$\sum_{s \in S} a_j = 1, \quad \text{for every } a_j \in A \tag{17}$$

1 For the inquisitive reader, these symbols are ['bli', 'blo', 'ama', 'ita', 'don', 'go', 'du', 'kap']

	Move red box right	Move red box left	...	Move green ball left
bli	$l_{1,1}$	$l_{1,2}$	$\dots$	$l_{1,8}$
blo	$l_{2,1}$	$\vdots$	$\ddots$	$\vdots$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
kap	$l_{8,1}$	$\dots$	$\dots$	$l_{8,8}$

Figure 14: An agent's language matrix. Each entry $l_{i,j}$ is the probability of action s_j being associated with symbol a_i.

Since agents do not have a previous language at the beginning of the game, every entry in the matrix is initialised to the same value $1/8$.

5.1.2 *Learning in the interaction*

A communicative interaction proceeds as follows:

1. A task is assigned randomly to the speaker. This task consists of performing an action, a_j, i.e. moving one of the objects in the middle cell to either the right or left neighbouring cell.

2. The speaker selects the symbol s_i where i is the maximum value of column j. If there are several symbols with the same value, then the speaker selects one of them randomly.

3. The listener receives symbol s_i and attempts to identify the action a_j by selecting the column j with the maximum value in row i. If several columns share the same value, the listener selects one of them randomly.

4. If the action is unsuccessful, the listener, should it decide to continue, chooses the next highest value in row i. This is repeated

until either the interaction succeeds or the listener decides to defect.

5. After a successful interaction the listener aligns its language to that of the speaker. It does this by updating the values of its language matrix using a learning mechanism common in language game literature called *lateral inhibition* (Steels and Loetzsch, 2012; Garcia-casademont and Steels, 2015), which increases the matrix entry $l_{i,j}$, where s_i is the symbol used and a_j is the correct action, while decreasing all other values in column j.

$$l_{ik}^{t+1} = \begin{cases} l_{ik}^{t} + \delta l_{i,k}^{t} & \text{if } k = j \\ l_{ik}^{t} - \delta l_{i,k}^{t} & \text{if } k \neq j \end{cases} \tag{18}$$

where $0 < \delta < 1$ is the *learning rate* and k is the column corresponding to the correct action. The column is then normalised to ensure that a distribution over the symbols is maintained.

Notice that, because agents choose maximum values deterministically rather than by sampling, they will *use* the same language whenever all language matrices have the same unique maximum value for each row and each column. If agents chose by sampling over columns or rows, then a common language would require that all matrices are the same permutation matrix. A permutation matrix contains a single 1 for each row and column and a 0 everywhere else.

5.1.3 *Language similarity*

A population has attained a common language when the language is fully consistent: any randomly chosen pair of agents in the population would communicate accurately and uniquely (see section 4.3.1). As mentioned above, the language matrices of all agents need not be equal for the population to reach full consistency; it suffices that every agent's matrix has the same unique maximum value for every row and column. Because agents hold distributions over the symbols in S for each action, one can obtain a measure of probability distance for each action, and then go on to average over all actions. The probability distance for each action can be computed using the Jensen-Shannon divergence:

$$JSD(a_j \in A) = H\left(\sum_{k=1}^{n} \pi_k \theta_{kj}\right) - \left(\sum_{k=1}^{n} \pi_k H(\theta_{kj})\right) \tag{19}$$

here n is the number of agents, A is the set of actions, θ_{kj} is agent k's distribution over the set of symbols S for action $a_j \in A$ and π_k is a weight assigned to distribution θ_{kj}. Since there is no reason to favour a particular agent, all distributions are assigned the weight $\pi^* = 1/n$. An average distance $D(P)$ for the language of population P is thus:

$$D(P) = \frac{\sum_{a_j \in A} JSD(a_j)}{|A|} \tag{20}$$

where |A| is the cardinality of set A.

The average Jensen-Shannon divergence ranges from 0 to 1, with 0 meaning that all distributions are equal for all actions. In effect, this requires that all language matrices are the same permutation matrix.

5.2 EXPERIMENTAL STUDY I

5.2.1 *Simulation setup*

As discussed in section 4.4.1, simulations are carried out on two groups of ten agents, made up of altruistic and mutualistic agents respectively. For all simulations the reward value, r, is fixed at 100. A simulation's parameters consist of an action cost, a_c, which is expressed as a fraction of r; and a coordination cost, c_c, a fraction of c_a. Both parameters are tested at discrete intervals $\Delta = 0.1$, over ranges $c_a = [0, 1.2]r$ and $c_c = [0, 1.2]c_a$. I run thirty simulations under every possible combination of both parameters. To test our hypothesis, I use as sample the number of interactions required by each group to reach full consistency. One caveat: to limit the running time of the simulations a maximum number of interactions was set at 150,000, and often a group does not reach full consistency by then. The simulations were executed in python 3.6.[2].

5.2.2 *Results*

5.2.2.1 *Learning rate*

Before focusing on analysing cost pairs I investigate the significance of the agents' learning rate, δ in equation 18. This is done by running thirty simulations under increasing values of c_a and δ, with a fixed $c_c = 0.1c_a$. Figure 15 shows the trajectories of consistency for two populations displaying altruistic and mutualistic behaviours respectively for increasing learning rates. The increase in consistency for altruistic agents is noticeably steeper and requires fewer interactions to reach full consistency. Figure 16 shows the median number of required interactions for 30 simulations. One can observe how the drop between the values obtained with a learning rate of 0.10 and 0.20 is very pronounced in the altruistic population. One can also notice that the trajectories are similar within each group, with the notable exception of $\delta = 0.1$ in the altruistic population. This suggests that the learning rate has no significant impact on how fast a population reaches full consistency, and differences between populations can be attributed to behaviour.

2 Simulations can be found in the following repository `https://github.com/mariano-mora/holistic_simulations`

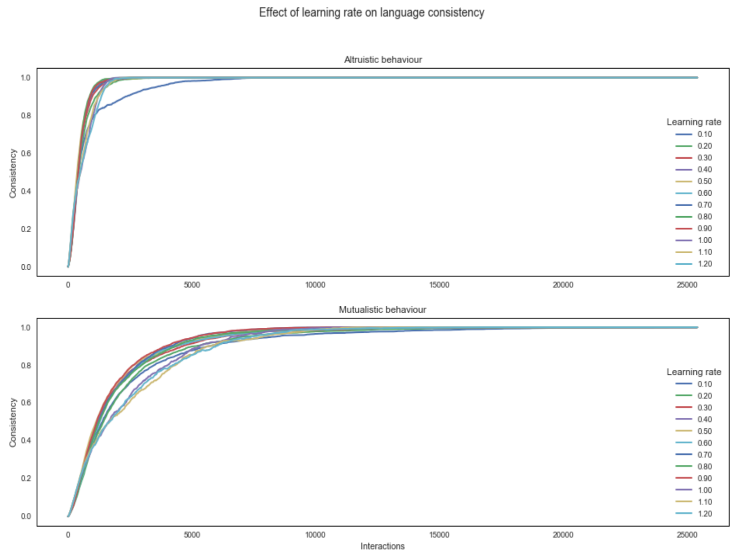


Figure 15: Consistency trajectories for two populations of agents displaying altruistic (top) and mutualistic (bottom) behaviour. Each curve represents the average over thirty runs of consistency under a different learning rate. Altruistic populations reach full consistency in shorter time, their linguistic evolution showing steeper trajectories. Notice how there does not appear to be a correlation between learning rate and speed of convergence within each population, except for $\delta = 0.1$ in the altruistic population. This suggests that the learning rate does not influence significantly the speed of convergence to a common language.

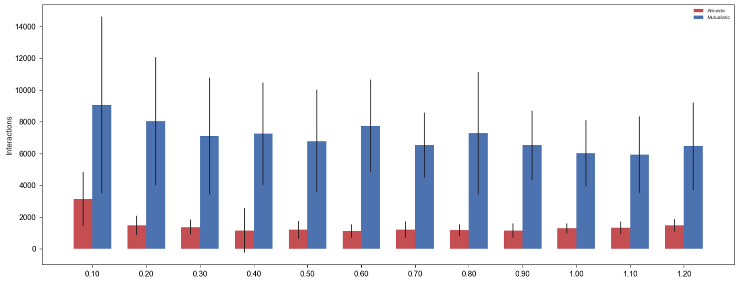


Figure 16: Number of interactions required to reach full consistency in two populations displaying altruistic and mutualistic behaviours respectively. Each bar represent the median of 30 runs. While the number of interactions required at each value of δ is very different in both populations, there is no significant difference for varying learning rates within the same population, except when $\delta = 0.1$ in the altruistic population.

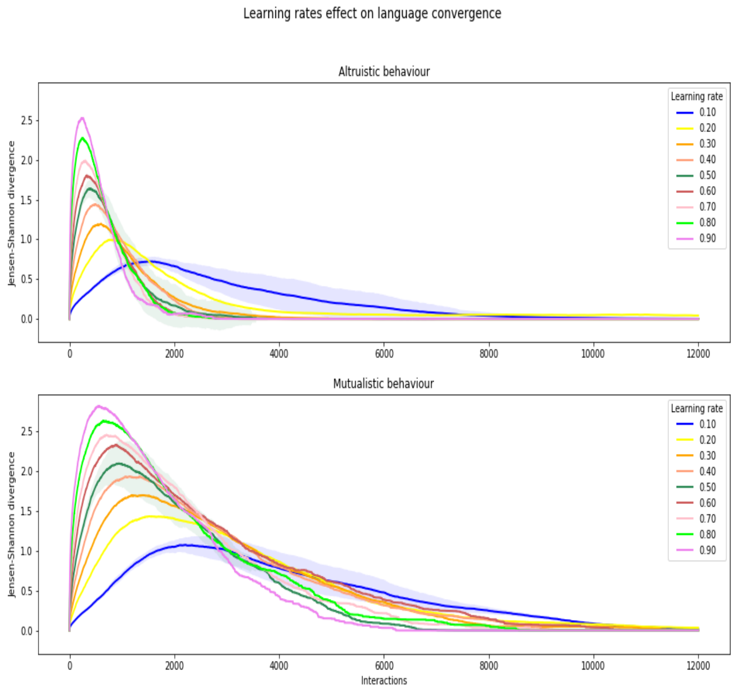


Figure 17: Average Jensen-Shannon linguistic distance as a function of increasing learning rates, δ, for populations of altruistic (top) and mutualistic (bottom) agents. Curves show the trajectories of the average Jensen-Shannon divergence under a range of learning rate values $\delta = [0.1.0.9]$. Action and coordination costs are fixed at $c_a = 0.4r$ and $c_c = 0.4c_a$. Each curve represents the mean of 30 simulations, shaded areas along each curve represent the standard deviation.

Figure 17 may help to illustrate how the learning rate affects convergence to a common language. Each curve represents the mean trajectory of the average Jensen-Shannon divergence under a different learning rate. Here action and coordination costs are fixed at $c_a = 0.4r$ and $c_c = 0.4c_a$. Because every agent's matrix is initialised to the same value (see above 5.1.1), the distance is initially 0. An agent's initial interaction is always going to require it to choose a symbol randomly. The distance grows as agents encounter new actions for the first time as speakers, since they will choose random symbols every time. Eventually the agents' languages reach a maximum dissimilarity, after which point they begin to converge. A higher learning rate has the effect of increasing the maximum distance and requiring fewer interactions to reach it. The number of interactions required to reach full convergence, where all language matrices are equal, does not change significantly with different learning rates. An exception is $\delta = 0.1$, which slows down the speed of convergence, while also reducing the maximum distance.

I compare the number of interactions required to reach full consistency in both populations for several learning rates under fixed $c_a = 0.5r$ and $c_c = 0.5c_a$. The results of the thirty simulations are not normally distributed (results of normality tests are shown in appendix 11). They are therefore tested non-parametrically. The null hypothesis is that the number of interactions for both populations are similarly distributed, whereas the alternative hypothesis is that the mutualistic group will require more interactions. Table 3 shows the results of right-tailed Mann-Whitney U tests for equality of distributions in both populations. Low p-values support a rejection of the null-hypothesis that both populations are similarly distributed and supports the alternative hypothesis. The similarities in statistics again suggest that the learning rate parameter does not significantly affect the results, which should be explained through the difference in cooperation strategies.

Learning rate	stat	p-value	ES	Σ_{alt}	Σ_{mut}
0.10	2378.5	3.73e-15	0.78	1396.5	3653.5
0.20	2498.0	3.97e-18	0.86	1277.0	3773.0
0.30	2499.0	3.72e-18	0.86	1276.0	3774.0
0.40	2459.0	3.99e-17	0.83	1316.0	3734.0
0.50	2493.0	5.35e-18	0.86	1282.0	3768.0
0.60	2500.0	3.50e-18	0.86	1275.0	3775.0
0.70	2500.0	3.50e-18	0.86	1275.0	3775.0
0.80	2500.0	3.51e-18	0.86	1275.0	3775.0
0.90	2500.0	3.49e-18	0.86	1275.0	3775.0
1.00	2500.0	3.51e-18	0.86	1275.0	3775.0
1.10	2500.0	3.52e-18	0.86	1275.0	3775.0
1.20	2500.0	3.52e-18	0.86	1275.0	3775.0

Table 3: Right-tailed Mann-Whitney U tests of number of interactions required to reach full consistency in two populations displaying altruistic and mutualistic behaviours respectively. The samples are obtained by running 30 simulations under each of the different learning rates on both populations. Very low p-values support rejecting the null hypothesis that language converges at similar speeds in both populations and accepting the alternative hypothesis that a greater number of interactions is required in populations displaying mutualistic behaviours. ES, Σ_{alt} and Σ_{mut} statistics are explained in appendix A.2

5.2.2.2 *Costs*

Figure 18 displays the number of interactions required to reach full consistency in both populations.

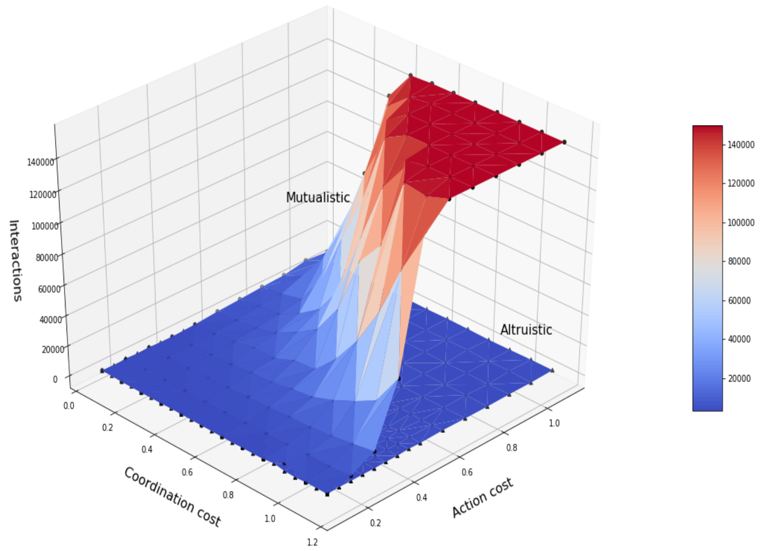


Figure 18: Number of interactions required to reach full consistency in two populations displaying altruistic and mutualistic behaviours over ranges of c_a and c_c. Each sample point represents the average number of interactions for thirty runs of each value in the action and coordination costs axis.

Each sample point represents the average of thirty runs under the pair of values in both the action cost and coordination cost axes. Because altruistic agents always help other agents regardless of the cost, the surface representing the average number of interactions is relatively flat over all the space. Mutualistic agents' decisions are affected by higher costs. This means that the number of interactions required to reach full consistency increases as either of the cost ratios increases. Notice that, because simulations limit the maximum number of simulations at 150,000, red areas in the graphic represent c_a and c_c parameter pairs under which the population does not converge to a common language.

This suggests that low costs provide mutualistic agents with an incentive to engage in helping behaviour, having learned to expect that such cooperation will result in a benefit to themselves. As costs increase, however, mutualistic agents will shy away from helping, and it will require more interactions for the lexicon to converge. The effect of increased costs may be evaluated by comparing the two groups at each of the different c_a and c_c values. The samples for each batch of simulations are not normally distributed, as shown in appendix A.1; I therefore use a non-parametric method to test the hypothesis. Because both populations are independent and my hypothesis expects larger values in the mutualistic population, I employ a right-tailed Mann-Whitney U test (Corder and Foreman, 2014). In this test, the null hypothesis states that the distributions for both populations are equal, whereas the alternative hypothesis is that the samples from a mutualistic population are greater. Table 4 displays the results of these tests. Included are measures of effect size, as well as the rank summation of each of the populations, all of which are explained in appendix A.2.

Low coordination or action costs result in p-values> 0.05, which do not allow us to reject the null hypothesis. However, as costs increase in either axis t-statistics decrease significantly, thus supporting the hypothesis that higher costs increase the number of interactions required to reach full consistency in a mutualistic population. Figure 19 may help to visualise the effect of increasing costs on whether p-values are below or above the α threshold. Interestingly, both populations display similar distributions when the coordination cost is low with respect to the action cost, even when the action cost is greater than the reward.

Figure 18 may be illustrative of the linguistic dynamics in both populations. 20a displays the linguistic evolution of a randomly chosen altruistic agent throughout its interaction life for all eight different

action	**coord**	stat	p-value	ES	Σ_{alt}	Σ_{mut}	**action**	**coord**	stat	p-value	ES	Σ_{alt}	Σ_{mut}
0.10	**0.05**	500.0	0.23	0.09	865.0	965.0		**0.65**	810.5	0.00	0.69	554.5	1275.5
	0.15	377.5	0.86	0.14	987.5	842.5		**0.75**	789.0	0.00	0.65	576.0	1254.0
	0.25	465.0	0.42	0.03	900.0	930.0		**0.85**	833.0	0.00	0.73	532.0	1298.0
	0.35	495.0	0.26	0.08	870.0	960.0		**0.95**	868.5	0.00	0.80	496.5	1333.5
	0.45	499.5	0.23	0.09	865.5	964.5		**1.05**	888.0	0.00	0.84	477.0	1353.0
	0.55	303.5	0.99	0.28	1061.5	768.5		**1.15**	898.0	0.00	0.85	467.0	1363.0
	0.65	467.0	0.40	0.03	898.0	932.0	**0.40**	**0.05**	465.0	0.42	0.03	900.0	930.0
	0.75	417.0	0.69	0.06	948.0	882.0		**0.15**	668.5	0.00	0.42	696.5	1133.5
	0.85	428.5	0.63	0.04	936.5	893.5		**0.75**	887.5	0.00	0.83	477.5	1352.5
	0.95	578.5	0.03	0.24	786.5	1043.5	**0.50**	**0.05**	459.0	0.45	0.02	906.0	924.0
	1.05	470.0	0.39	0.04	895.0	935.0		**0.35**	877.0	0.00	0.81	488.0	1342.0
	1.15	556.0	0.06	0.20	809.0	1021.0		**0.65**	892.0	0.00	0.84	473.0	1357.0
0.20	**0.05**	350.0	0.93	0.19	1015.0	815.0		**1.05**	900.0	0.00	0.86	465.0	1365.0
	0.15	495.0	0.26	0.08	870.0	960.0	**0.60**	**0.05**	659.0	0.00	0.40	706.0	1124.0
	0.25	536.0	0.10	0.16	829.0	1001.0		**0.55**	900.0	0.00	0.86	465.0	1365.0
	0.35	505.0	0.21	0.10	860.0	970.0		**0.95**	600.0	0.00	0.86	465.0	810.0
	0.45	613.5	0.01	0.31	751.5	1078.5	**0.70**	**0.05**	733.5	0.00	0.54	631.5	1198.5
	0.55	555.5	0.06	0.20	809.5	1020.5		**0.45**	900.0	0.00	0.86	465.0	1365.0
	0.65	554.0	0.06	0.20	811.0	1019.0		**0.95**	750.0	0.00	0.90	465.0	1075.0
	0.75	636.5	0.00	0.36	728.5	1101.5	**0.80**	**0.05**	802.5	0.00	0.67	562.5	1267.5
	0.85	598.0	0.01	0.28	767.0	1063.0		**0.75**	750.0	0.00	0.90	465.0	1075.0
	0.95	697.5	0.00	0.47	667.5	1162.5	**0.90**	**0.05**	778.0	0.00	0.63	587.0	1243.0
	1.05	724.0	0.00	0.52	641.0	1189.0		**0.55**	750.0	0.00	0.88	465.0	1075.0
	1.15	783.0	0.00	0.63	582.0	1248.0		**1.15**	690.0	0.00	0.89	465.0	966.0
0.30	**0.05**	433.5	0.60	0.03	931.5	898.5	**1.00**	**0.05**	569.0	0.00	0.75	241.0	1034.0
	0.15	442.5	0.55	0.02	922.5	907.5		**0.55**	320.0	0.00	0.88	210.0	456.0
	0.25	520.5	0.15	0.13	844.5	985.5		**0.85**	300.0	0.00	0.88	210.0	420.0
	0.35	585.5	0.02	0.26	779.5	1050.5	**1.10**	**0.05**	551.0	0.00	0.70	259.0	1016.0
	0.45	644.0	0.00	0.37	721.0	1109.0		**0.45**	460.0	0.00	0.92	210.0	736.0
	0.55	705.0	0.00	0.49	660.0	1170.0		**0.95**	460.0	0.00	0.93	210.0	736.0

Table 4: Mann-Whitney right-tailed results for different action and coordination costs. Columns show the Mann-Whitney U statistic, p-value, effect size, rank summation for the altruistic population and rank summation for the mutualistic population. The null hypothesis H_0 is that both populations are stochastically similar. The alternative hypothesis H_A is that the number of interactions required by the mutualistic populations are greater than the number required by the altruistic populations. ES , Σ_{alt}, Σ_{mut} statistics are explained in appendix A.2

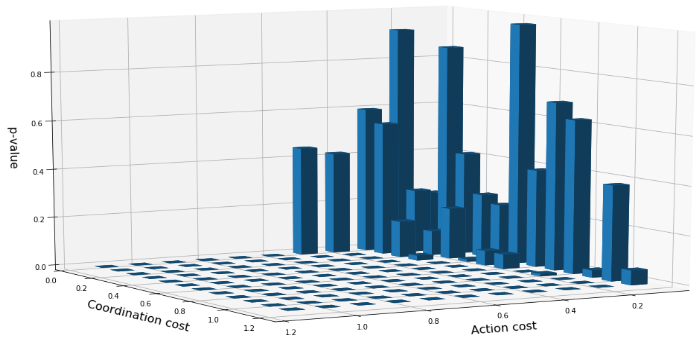
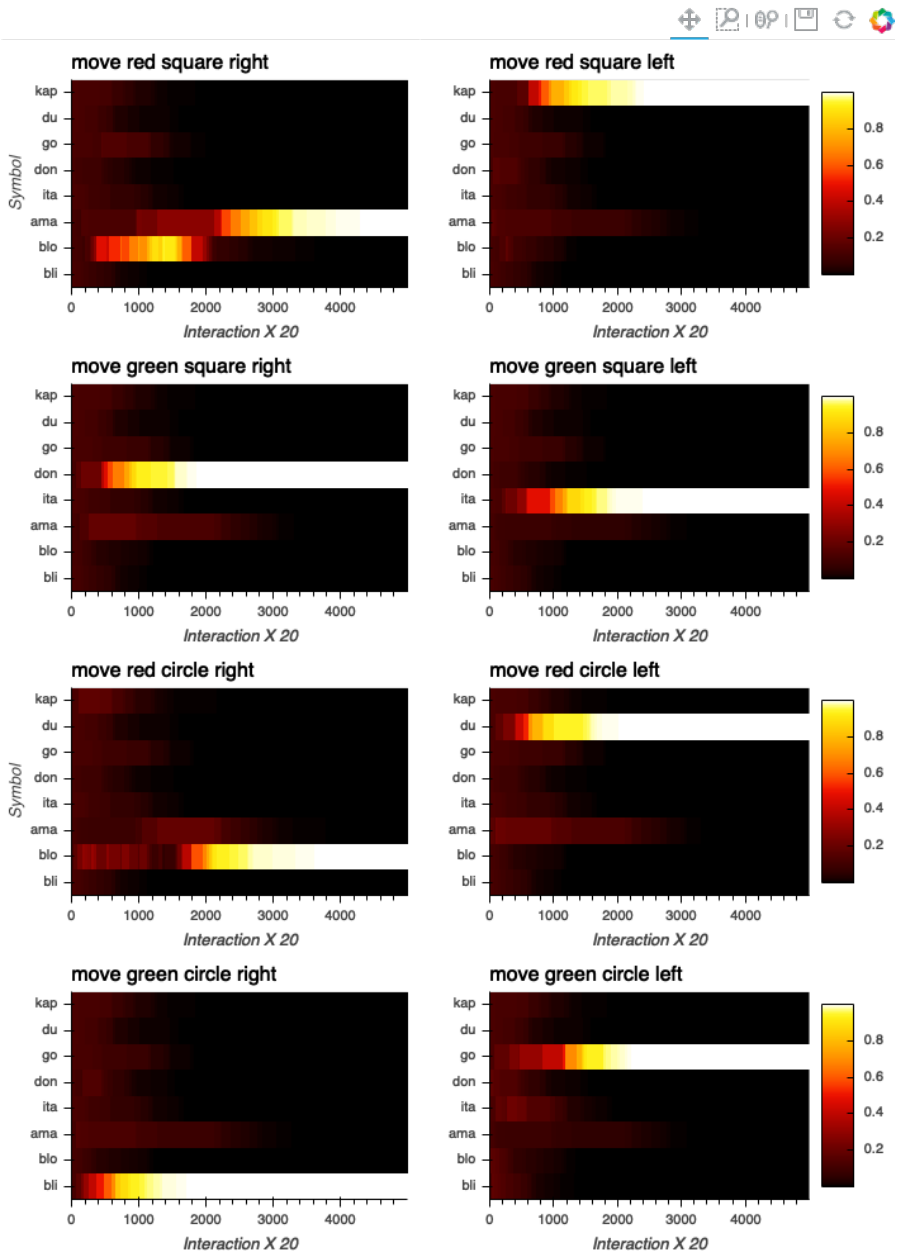
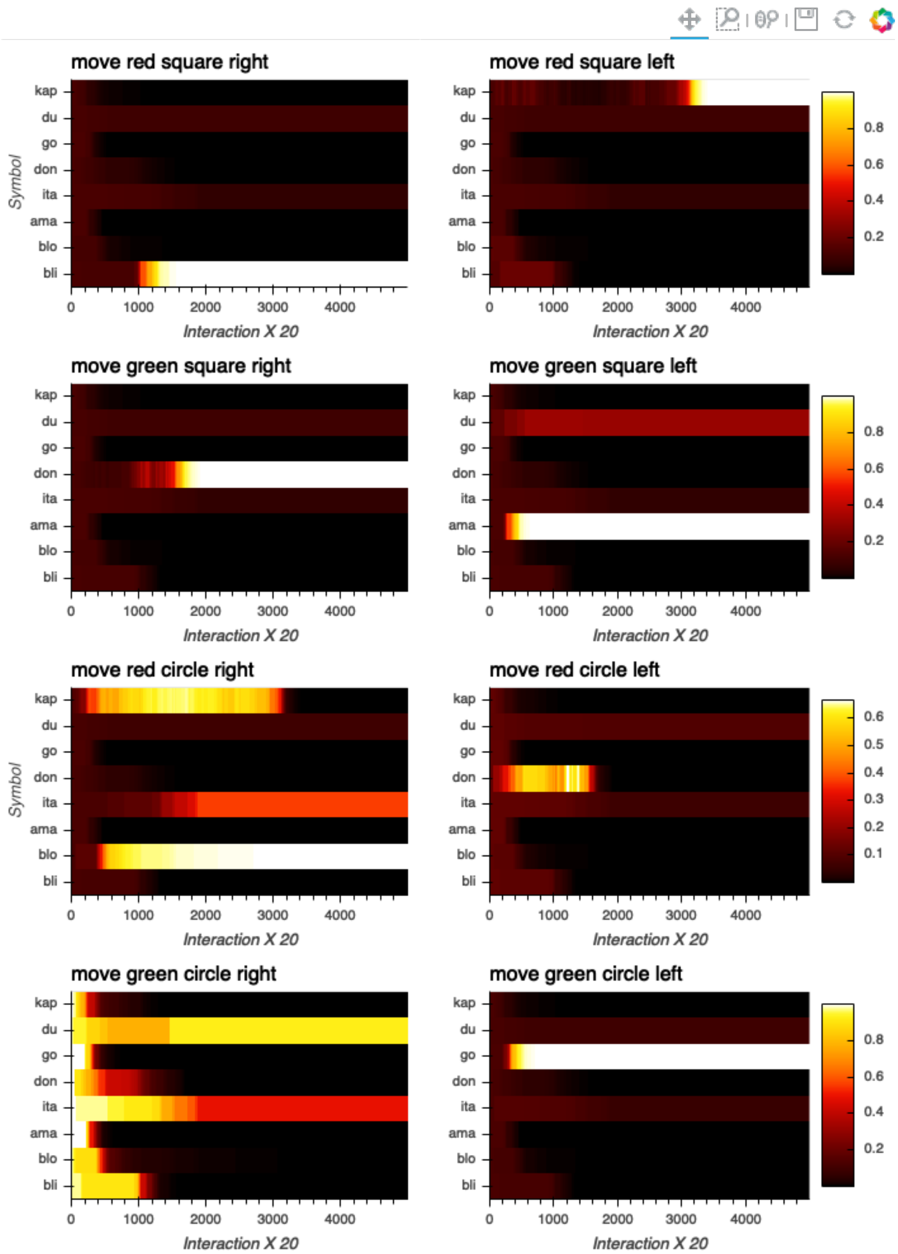


Figure 19: p-values for right-tailed Mann-Whitney U tests of the number of interactions required to reach full consistency over different action and coordination costs in two populations of agents displaying altruistic and mutualistic behaviours respectively. P-values greater than $\alpha = 0.05$ support the null-hypothesis that both populations are similar. When both action and coordination costs are low, there is no significant difference between altruistic and mutualistic behaviours' convergence to a common language. A low action cost can make up for high coordination costs, whereas, significantly, a low coordination cost means that both behaviours are similar even when the action cost is half of the reward.

actions. After an initial period in which the distributions are similar, a single action-pair association eventually wins out, as shown by the fact that each action has a single different active row. This cannot be said of the language evolution of a mutualistic agent, as shown in 19b. Here the agent cannot decide whether it should move the red ball or the green ball right when receiving the symbol 'ita'.



(a) Altruistic agent



(b) Mutualistic agent

Figure 18: Language evolution of two agents. The figure displays the evolution of the distributions of over symbols $s_i \in S$ for all eight actions. (a) shows the language of an agent randomly chosen from the altruistic population, whereas (b) is the language of a randomly chosen mutualistic agent. Here the mutualistic population does not converge to a common language, since agents cannot decide which symbol corresponds to several actions.

5.3 EXPERIMENTAL STUDY II

As in the previous study, this experimental study explores the effect of altruistic and mutualistic behaviours on the emergence of language. In this case, however, both types of behaviour coexist in one population. As described in section 4.4.2, agents play an evolutionary game, where agents are allowed to evaluate and change their cooperation strategy through a simple imitation process.

This study introduces a further parameter: the initial proportion of altruistic agents, α.

As in the previous study, a measure of the spread of a shared language is obtained through the language consistency.

5.3.1 *Simulation setup*

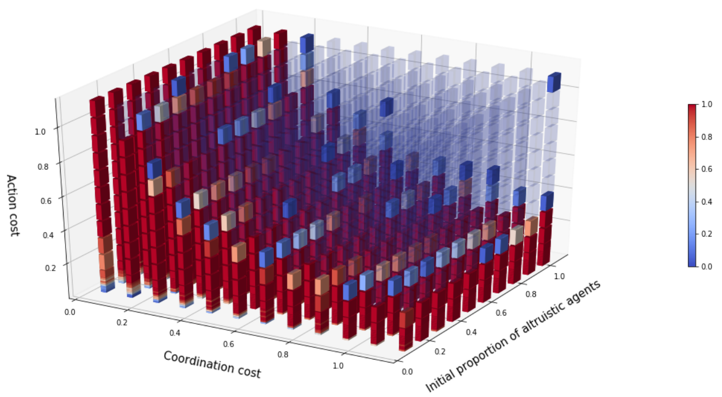
I have run simulations of the Coordination Language Game (CLG) on populations of 100 agents. Initially, every agent is either altruistic or mutualistic. Each simulation explores the evolution of the population under different values of three parameters: the action cost, c_a, the coordination cost, c_c, and the initial proportion of altruistic agents in the population, α. I explore the range of all three parameters in increasing discrete intervals Δ, ranging from 0.05 to 1.15 in the case of c_a and c_c and from 0.05 to 0.95 for α. This means that both costs are eventually greater than the reward. Because the model showed greater variance with low action cost values I have used a finer-grained interval in that range:

$$\Delta = \begin{cases} 0.01, & \text{for } 0 < c_a \leq 0.15 \\ 0.10, & \text{for } 0.15 < c_a \leq 1.15 \end{cases}$$

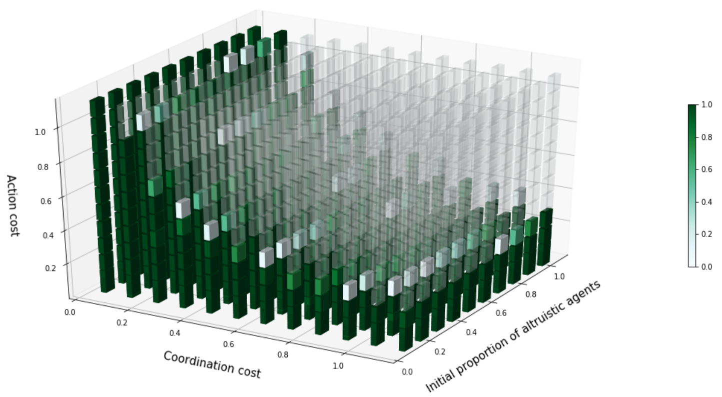
The revision protocol is described in section 4.4.2. Briefly, randomly selected agents change their behaviour by imitating more successful individuals. In this study, 5 imitators and 5 role-models were selected every 40 interactions.

Agents remember the cost of their last interaction only, that is $n = 1$ in equation 13. Every simulation was run 20 times and stopped when the model displayed no more dynamic behaviour, because the population had fixated at one of the possible strategies *and* the agents had converged to a common language. A maximum number of interactions was set at 150,000.

5.3.2 *Results*



(a) Percentage of simulations that fixate at altruism



(b) Percentage of simulations that converge to common language

Figure 19: Figure (a) displays the cooperation strategy fixations. Each cube shows the results of 20 simulations under a parameter triplet $\{c_a^i, c_c^j, \alpha^k\}$. The cube's colour displays the percentage of simulations that fixated at either strategy. Percentages range from all mutualistic (dark blue) to all altruistic (bright red). To facilitate viewing I have shaded all cubes representing parameter triplets under which all runs fixated at a mutualistic strategy. Figure (b) displays the percentage of simulations under each parameter triplet in which full linguistic consistency was reached. I have shaded the simulations where no common language was reached to facilitate viewing. Note the dissimilarity between both graphs along very low values of the action cost.

5.3.2.1 *Population dynamics*

Every simulation fixated at one of the cooperation strategies, i.e. all agents had the same strategy at the end of every simulation. This suggests that the game has no internal equilibrium point in which altruistic and mutualistic agents can coexist sustainably in a population. Which strategy dominates depends, as expected, largely on the costs and to a lesser degree on the initial number of altruistic agents.

Figure 19a displays the dominant strategies as a function of action and coordination costs, as well as initial proportion of altruistic agents. Each cube shows the results for a parameter triplet $\{c_a^i, c_c^j, \alpha^k\}$, its colour displaying the percentage of runs that fixated at either strategy, where 1 (bright red) indicates that all runs fixated at an altruistic strategy. To facilitate viewing I have removed cubes representing triplets where all 20 runs fixated at a mutualistic strategy.

The figure shows the interplay between the cost of carrying out the action and the cost of coordinating it.

- As costs increase mutualism becomes a dominant strategy. If $c_a > 0.35r$ *and* $c_c > 0.75c_a$ mutualistic strategy offers a fitness advantage that will make altruistic agents copy them.

- Altruism is dominant if $c_c < 0.25c_a$ for higher values of the action cost, i.e. $c_a > 0.25r$. A low coordination cost will result in a fitness advantage for altruistic agents even for $c_a > r$.

- Low values of both action and coordination costs show a greater variance in fixating strategies. Mutualism will be advantageous when both values are at their lowest: $c_a = 0.05r$ and $c_c = 0.05c_a$.

- Fitness is sensitive to the initial proportion of altruistic agents, particularly if both costs are low. Mutualism will spread through the population even if only 5% of the population are initially altruistic. At low cost values mutualistic agents will interact with a high probability, which means that they are very likely to share the costs, thus increasing their fitness and reducing the number of attempts required in future interactions.

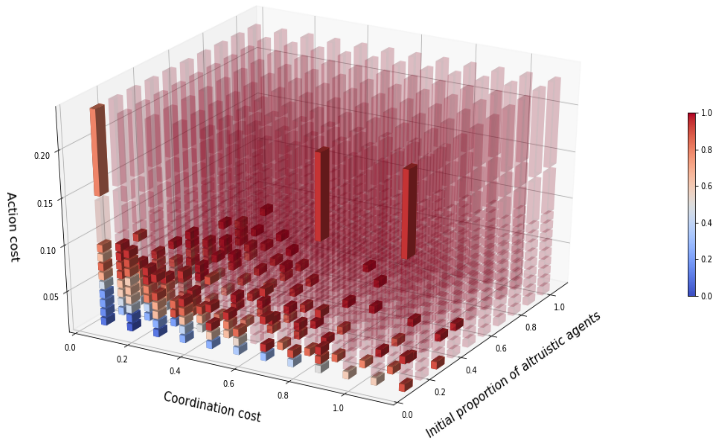


Figure 20: Detail of cooperation strategy fixations for $c_a < 0.25r$. This figure is a closer look at the low values of c_a taken from figure 19a. In this case cubes representing simulation in which every run fixated at altruistic behaviour have been shaded to facilitate viewing.

5.3.2.2 *Language stability*

Figure 19b shows the percentage of simulations per parameter triplet where the population reached a common, fully consistent language. As in figure 19a, each cube represents a parameter triplet and its colour displays the percentage of runs in which the population reached full consistency. Cubes representing parameters under which none of the simulations reached consistency are shown as shades to facilitate viewing.

Results are very similar to those obtained for the population dynamics, suggesting that high costs will not allow agents to establish a common language. A significant difference can be found along the lowest action cost value, $c_a = 0.05r$. Figure 20 shows the percentage of fixating strategies for parameter triplets satisfying $c_a < 0.25r$, a detail of the values shown in figure (a). Mutualistic behaviour can dominate in a population under such restricted circumstances and still converge to a common language, if the initial proportion of altruistic agents is less than 35% of the population.

- As costs increase it becomes more and more unlikely that language will converge. Similarly to the results shown in figure (a), if $c_a > 0.35r$ and $c_c > 0.75c_a$ it is unlikely that the population will share a common language after 150,000 interactions.
- For low coordination costs, i.e. $c_c < 0.25c_a$, the population is very likely to converge to a common language, allowing even for very expensive actions.
- Low costs will result in language convergence regardless of the dominant cooperation strategy. As shown saw in figure (a), low action and coordination costs result in a fitness advantage for mutualistic agents, whose commitment to helping suffices to allow a common language to be established.
- Language convergence is also sensitive to the initial proportion of altruistic agents in the population. It is noticeable that if 95% of the agents are initially altruistic the population can reach a common language even if communicating is costly with respect to the cost of carrying out the action, for example, if $c_c < 1.05c_a$, as long as $c_a < 0.45r$.

5.4 SUMMARY

This chapter has reported on two experimental studies on the impact of altruistic and mutualistic cooperative behaviour on the emergence of a common language. The first study compares the speed at which language converges in two independent populations, one made up of altruistic agents, while agents in the other group are exclusively mutualistic. Taking as samples the number of interactions required to reach full consistency, I tested the hypothesis that language will converge faster in populations of altruistic individuals. Results of non-parametric hypothesis testing strongly suggest that this hypothesis is true, if the costs of performing and coordinating the joint action are high enough. Results also point at the importance of low coordination costs. If the cost of coordinating the language is low enough ($c_c < 0.10c_a$), a mutualistic population can develop a shared language at a speed similar to that of an altruistic population, even if the cost of performing the action is half of the reward.

These results stand also in a situation in which altruistic and mutualistic individuals interact with each other in a mixed population. The second study reported in this chapter suggests that at low action and coordination costs, mutualistic agents enjoy a fitness advantage. Mutualistic behaviour spreads throughout the whole population and a common language emerges. Altruism is the dominant strategy if the number of altruistic agents is initially more than 30% of the population. If $c_a > 0.25r$, however, mutualistic behaviour dominates, regardless of the cost of coordinating actions. In this case, the population will not develop a common language.

6

SECOND CASE: EMERGENCE OF COMPOSITIONAL STRUCTURES

This chapter reports on two experimental studies aimed at investigating the effect of altruistic and mutualistic behaviours on the emergence of compositional structures in language. These two studies continue and extend the experiments described in chapter 5 above. In this set of simulations, however, instead of associating symbols to actions, agents use the utterances they hear to build an internal grammar which includes compositional rules.

The studies follow the pattern set by the two previous experiments and discussed in sections 4.4.1 and 4.4.2. An initial experiment simulates the language evolution in two independent groups of altruistic and mutualistic agents respectively. This type of experiment allows me to compare the language evolution in both groups.

I hypothesise that altruism will have a positive impact on the emergence and development of compositional structures within a population. This language will be shared by a larger fraction of the population than in the case of a mutualistic population. More specifically, the consistency of the language will be greater in a population of altruistic agents.

In the second experiment, language evolves in a mixed population, in which both behaviours compete for dominance. The aim is to determine whether, and under what conditions, such a population will develop a consistent language.

R_1:	S[s1+s2+s3] → A[s1=?], G[s2=?], E[s3=?]	1.000
R_2:	S[s1+s2+s3] → G[s1=green], A[s2=?], E[s3=?]	0.000
R_3:	S[s1+s2+s3] → E[s1=?], A[s2=?], G[s3=?]	0.000
R_4:	S[s1+s2] → A[s1=?], B[s2=?]	0.000
R_5:	S[s1+s2] → F[s1=?], E[s2=?]	0.000
R_6:	F[s1+s2] → A[s1=?], G[s2=?]	0.550
R_7:	H[s1+s2] → A[s1=?], E[s2=?]	0.001
R_8:	B[s1+s2] → E[s1=?], G[s2=?]	0.001
R_9:	A[s=ball] → “x"	1.000
R_{10}:	G[s=green] → “e"	1.000
R_{11}:	E[s=right] → “m"	1.000
R_{12}:	B[s=(red,right)] → “wx"	0.000
R_{13}:	S[s=(green,ball,right)] → “hth"	0.399
R_{14}:	S[s=(ball,right,red)] → “jxpce"	0.196

Figure 21: An example grammar. Each rule's left hand side is of the form $Syn[Sem]$ where *Syn* is a syntactic category (here S, A, B, etc.) and *Sem* is a set of semantic attributes. *Sem* may be underspecified as to semantic category, or fixed to specific one (*shape, colour, direction*). *Sem* may also be restricted to a single value or apply to the two different values that belong to a category, shown here as a question mark. The right hand side consists of either a sequence of similarly specified daughter or a string terminal. Finally, each rule is weighted from 0 to 1.

6.1 AGENT'S LANGUAGE

The agents' linguistic processing relies heavily on the language experiments developed by Vogt (2005), discussed on section 2.4.2.1. This work, in turn, borrows from the linguistic models of Kirby (1998), Kirby (2001), and Kirby (2002). This section begins by describing the linguistic form of an agent's internal grammar. Agents use their grammar as they develop it, encoding and decoding utterances to refer to actions.

6.1.1 *An agent's grammar*

As discussed in section 4.2.1.1, agents know three semantic categories: *shape, colour* and *direction*. They have no notion of verbs, but such a notion is not required. They know that objects are there to be moved somewhere.

Figure 21 shows an agent's internal language. It is a probability attribute grammar (PAG) (Stolcke, 1994). A PAG is an extension of stochastic context free grammar which can assign a set of features to a non-terminal. Following Kirby (2000) a PAG contains:

1. a set of non-terminal symbols $\mathcal{N}$
2. a set of terminal symbols Σ
3. a start non-terminal $S \in \mathcal{N}$
4. a set of production rules $\mathcal{R}$ of the form $X \rightarrow \lambda$, where $X \in \mathcal{N}$ and $\lambda \in (\mathcal{N} \cup \Sigma)$
5. production counts $C(r)$ for all $r \in \mathcal{R}$

Each production rule can contain a semantic part made up of attribute-value pairs. The left hand side of a rule is of the form $Syn[Sem]$ where Syn is a syntactic category and Sem is a set of semantic attributes. Sem may be fixed to one of the semantic categories defined in section 4.2.1.1: *shape, colour* and *direction*. It can also be assigned to two or three semantic categories. Sem may also be restricted to a single value, or it can take either of the two possible values in each semantic category.

Example 1

Imagine an agent hears the utterance "wxy" and learns that it means 'red ball right'. In a subsequent interaction it learns the utterance "wxz" with meaning 'red ball left'. The learner realises that the parts of the meaning these two utterances have in common correspond to the semantic categories *colour* and *shape*. It also comes to the conclusion that the symbols "y" and "z" are two different values belonging to the semantic category *direction*. The agent then creates the following simple grammar:

R_1: A[s=(right)] $\rightarrow$ "y"

R_2: A[s=(left)] $\rightarrow$ "z"

R_3: B[s=(red, ball)] $\rightarrow$ "wx"

R_4: S[s1+s2] $\rightarrow$ B[s=(red,ball)], A[s=?]

The agent has created two new syntactic categories. B has fixed semantic content, it is connected to two specific semantic categories and those particular values. R_4 states that, whenever the agent needs to refer to something that has attribute values **red** and **ball**, it can use the expression "wx" followed by something else. The grammar includes a further new syntactic category, A, which is linked uniquely to the semantic category *direction*. This syntactic category, however, is not fixed to any semantic values. The agent knows this because it has already encountered two examples with different meanings. Rule R_4 states that, after using "wx" for **red ball**, the agent is allowed to use any of the values associated to syntactic category A.

Syntactic rules associated to two or three semantic categories are very common in the languages developed by the agents in this game. Because agents have no initial linguistic knowledge whatsoever, they cannot construct utterances in their initial interactions. In this case the agent will invent an utterance that refers to the action it has to perform. This action contains all three semantic categories, it is a holistic expression. Kirby (2000) refers to this as Stage I in the game's linguistic evolution. The grammar in example 2 corresponds to Stage

II, in which semantic categories are lumped together in a syntactic category, usually with fixed semantic values.

Example 2

Imagine further that the same agent, who already has the grammar in example 1, is given the utterance "wdz" meaning 'red box left'. It compares the first two symbols of this utterance with the string terminal in rule R_3 and reaches the conclusion that it can add another syntactic category to its grammar, one that is associated to the semantic category *colour* with the fixed value **red**. In fact, the agent adds four new rules, because it now knows that the symbol "x" refers to *shape*, as does the symbol "d". The new rules are:

R_5: C[s=red] $\rightarrow$ "w"

R_6: D[s=ball] $\rightarrow$ "x"

R_7: D[s=box] $\rightarrow$ "d"

R_8: B[s1+s2] $\rightarrow$ C[s=red], D[s=?]

Notice how rule R_8 is a split of rule R_3, since both rules have the same syntactic category, only now R_8 is not entirely fixed to the value **ball**. The agent will create a further compositional rule which applies this new knowledge:

R_9: S[s1+s2+s3] $\rightarrow$ C[s=red], B[s=?], A[s=?]

This is Stage III in Kirby (2000), and the utterance has been completely atomised.

A further example is provided in the next section, in which I discuss the mechanisms used by agents to induce their grammar.

6.1.2 *Grammar induction*

Agents build their internal grammar using the following mechanisms:

1. **Incorporation**: When a listener cannot decode an utterance it attempts to guess the right action. If correct, the agent adds the

association between the action and the utterance as a *holistic* rule. R_{13} in the grammar shown in figure 21 is an example of a holistic rule.

2. **Chunking**. If the listener identifies two rules which share a common semantic value and common substrings at beginning or end of their terminal strings, it associates the common substring to the common meaning. This is the mechanism at work in example 1 above. As another example, if the agent has learned the following two holistic rules:

   R_i: S[s=(ball,right,red)] $\rightarrow$ "jxpce"

   R_j: S[s=(ball,right,green)] $\rightarrow$ "jxpcd"

   it creates three new rules to account for the common as well as the non-common parts.

   R_k: H[s=(ball,right)] $\rightarrow$ "jxpc"

   R_l: G[s=red] $\rightarrow$ "e"

   R_m: G[s=green] $\rightarrow$ "d"

   Algorithm 1 is a pseudo-code description of the chunking process. An agent creates three new rules, one with the common semantic and symbolic parts of both input rules, and another two rules for the unique parts. Neither input rule is discarded.

   I follow Vogt (2005)'s alignment method in searching for common sub-strings at the beginning and end of utterances. In contrast to Kirby (2002)'s model, the learner does not remove the original holistic rules. Keeping associations between words and meanings is common practice in language game models, where the predominance of particular rule is determined by the usage of the agents, and selection of certain constructions over others is determined by their contribution to successful interactions (Steels, 1996; Steels, 2000b).

Algorithm 1 Chunking grammar rules

Input: A grammar G with N rules $R_1 \dots R_N$

function Chunking
    for $R_i \in G$ **do**
        for $R_j \in G$ **do**
            $String_i \leftarrow R_i$[terminal symbol]
            $a_i[] \leftarrow R_i$[semantic values]
            $String_j \leftarrow R_j$[terminal symbol]
            $a_j[] \leftarrow R_j$[semantic values]
            if
                $String_i$ and $String_j$ begin or end with the same substring
                AND
                $a_i[], a_j[]$ share at least one semantic value ($a_i \cap a_j \neq \emptyset$)
then
                create new rules
                R_{N+1} with symbol = common substring and semantic attributes = common semantic values
                R_{N+2} with terminal symbol = non-shared substring of R_i[terminal symbol], and semantic values = non-shared semantic values from R_i
                R_{N+3} with terminal symbol = non-shared substring of R_j[terminal symbol], and semantic values = non-shared semantic values from R_j
            end if
        end for
    end for
end function

3. **Generalisation**: If the agent identifies two rules which differ only in one meaning, it generalises to a more comprehensive rule that includes all semantic values contained in both rules. For example, the following two rules contain the same syntactic categories in the same order. They differ only in that R_n contains the semantic value **ball** whereas R_m contains **box**:

R_n: S[s1+s2+s3] $\rightarrow$ A[s1=ball], G[s2=green], E[s3=right]

R_m: S[s1+s2+s3] $\rightarrow$ A[s1=box], G[s2=green], E[s3=right]

Generalisation expands the semantic value associated to syntactic category A to allow any value of semantic category *shape*:

R_p: S[s1+s2+s3] $\rightarrow$ A[s1=?], G[s2=green], E[s3=right]

Algorithm 2 runs through the steps employed by an agent to generalise non-terminal rules. The agent effectively choose the rule with the greatest weight and adds the new meaning to its set of semantic values. The other rule is discarded.

Algorithm 2 Generalising grammar rules. An agent adapts a rule to fully determine a semantic category if it observes the same syntax being applied to the category's two possible values.

Input: Two rules $R_1, R_2 \in$ Grammar G

Output: Both rules have non-terminal symbols

```
function GENERALISING
    Symbol_1 ← R_1[non-terminal symbol]
    a_1[] ← R_1[semantic values]
    Symbol_2 ← R_2[non-terminal symbol]
    a_2[] ← R_2[semantic values]
    if
            Symbol_1 = Symbol_2
            AND
            only one value is different in a_1[] and a_2[]
            AND
            the single different values in both a_1[], a_2[] belong to the same
            semantic category
    then
        choose rule R_max(R_1[weight],R_2[weight]) and add to its set of meanings the
    value contained in the other rule and remove the other rule.
    end if
end function
```

4. A merge process simply identifies repeated rules in a grammar. Rules that have the same syntax, or expression, and the same semantic values are considered to be the same. The agents chooses the one with the greatest weight and discards the other one.

5. Syntactic categories are not merged, but rather are the result of splitting common and non-common parts of terminal expressions. If two expressions have a common substring and share one semantic value, then agents assume that the rest of the string corresponds to the rest of the semantic values, and hence the semantic categories. Thus, the two semantic categories are "merged", although, strictly speaking they were never separated.

6.1.3 *Linguistic interaction*

An agent makes use of its grammar as it builds it.

- **Encoding**: The speaker knows which action is to be carried out, and it produces an utterance to communicate it to the listener. It does this by employing the linguistic knowledge it has acquired in previous interactions. This process follows three steps:
  1. The speaker first looks for rules in its grammar that contain *all* the semantic values in the action. These rules can be compositional or holistic. Taking the grammar in figure 21, an agent would have several choices to utter the command "Move green ball right": it could choose between R_1, R_2 or R_3 to concatenate rules $R_9 \circ R_{10} \circ R_{11}$ in different order. It could also use holistic rule R_5. The agent would choose R_1 because of its greater weight.
  2. If the speaker cannot find a rule that contains all semantic categories and values required, it looks for the rule that contains the highest number of semantic values and *invents*

a string for the values that are missing. For example: if the action is "Move red box right" the agent is not be able to find a rule that contains all three values, since it has not learned a rule for the single value **box**. It can however exploit the fact that it has learned a word for **red right** and employ R_{12}. It then creates a new string for the missing part and adds it to the string "iwj".

3. If the agent cannot find a rule that contains any of the values required, it produces a holistic expression that made out of random strings. For example, if the agent is to produce an utterance for the action "Move red box left" it will not find any rules that contain the three values, neither fully nor partly. In this case it produces a new string that contains all the values.

- **Decoding**: After receiving the utterance from the speaker, the listener tries to guess the action. It can guess the most likely one by identifying elements in the utterance that coincide with its own internal grammar. It then ranks all possible actions according to the weight of the rules used to decode the utterance. If the agent cannot interpret the utterance or if several rules are equally weighted, then it chooses an action randomly.

6.1.4 *Learning*

Successful interactions allow the listener to acquire or induce new rules. If an agent has not been able to decode the utterance, it adds it to its grammar as a holistic rule. Otherwise, it reinforces the correct rules through lateral inhibition:

$$\rho_i^{t+1}) = \begin{cases} \rho_i^t(1+\delta) & \text{if successful} \\ \rho_i^t(1-\delta) & \text{otherwise} \end{cases} \tag{21}$$

where $\delta = 0.9$ is a constant *learning rate* and ρ_i^t is the weight of rule i at interaction t. If the rule chosen is compositional, then all daughter rules employed are also reinforced. All other rules with the same left hand syntactic elements and semantic content are inhibited. Normalisation is performed also over rules with similar syntactic structure.

6.2 linguistic measures

6.2.1 *A note on consistency*

The definition of consistency as stated in section 4.3.1 is valid for languages with compositional structures. In contrast to the holistic languages explored in the previous chapter, two agents may communicate accurately about an action using a compositional language without producing the same utterance. It is enough that both agents understand each other's utterance accurately. Consider two agents who have learned the following rules:

Agent 1

R_1	:	S[s1+s2+s3] $\rightarrow$ A[s1=red], B[s2=ball], C[s3=right]	1.0
R_2	:	A[s=red] $\rightarrow$ "w"	1.0
R_3	:	B[s=ball] $\rightarrow$ "x"	1.0
R_4	:	C[s=right] $\rightarrow$ "y"	0.9
R_5	:	C[s=right] $\rightarrow$ "z"	0.1

Agent 2

R_1	:	S[s1+s2+s3] $\rightarrow$ A[s1=red], B[s2=ball], C[s3=right]	1.0
R_2	:	A[s=red] $\rightarrow$ "w"	1.0
R_3	:	B[s=ball] $\rightarrow$ "x"	1.0
R_4	:	C[s=right] $\rightarrow$ "y"	0.1
R_5	:	C[s=right] $\rightarrow$ "z"	0.9

When referring to action "Move red ball right", agent 1 concatenates rules $R_1 \circ R_2 \circ R_2 \circ R_3$ to produce the utterance "wxy". Using the scores of these four rules produces a unique maximum value of 2.9. Agent 2 concatenates rules $R_1 \circ R_2 \circ R_2 \circ R_4$ to produce utterance "wxz", with the same unique maximum value. However, both agents understand each other's utterances.

6.2.2 *Compositional spread*

For the agents in these experiments a fully developed compositional language must include a rule that prescribes how to concatenate three syntactic categories and terminal expressions for all six different semantic values. The processes of chunking ensures that strings are split into atomic values which cannot be split further and compositional rules are produced that indicate the ordering of the atomic elements. The process of generalisation ensures that, given enough samples, agents learn to apply the rule to the six different atomic words. I refer to this as *atomic compositionality*, as the rules prescribe how to compose together atomic words.

Two agents have a similar atomic compositional language if their internal grammars include such rules, and their maximally weighted atomic and compositional rules are the same, i.e. their symbols are equal and they apply to the same semantic values. A measure of how commonly shared a language is in a population can be obtained by counting the members in the population who have similar maximally weighted rules for each of the six possible atomic values, as well as the same compositional rule. A measure of the spread is then obtained by averaging over all seven possible maximally weighted rules.

More formally, a rule is a maximal atomic rule if it is terminal rule whose semantic value is only one of the six meanings and no other rule with the same semantic value is maximally weighted.

$$\begin{aligned} \exists r_{max} := r \in G \wedge r.x \in \Sigma \wedge r[sym] \in W \\ \wedge\, r.weight \approx 1. \\ \wedge\, \exists! y(y[sym] = r[sym] \wedge y.weight \approx 1.) \end{aligned} \tag{22}$$

where G is a grammar, Σ is the set of terminals of the grammar and W is the set of six semantic values. An agent's grammar contains a set A of maximal atomic rules if it contains at least one maximal atomic rule. A maximal compositional rule can be similarly defined, only with a compositional syntactic structure of three daughter rules and a semantic content containing every semantic value.
The compositional similarity between two grammars is the number of elements they have in common, averaged over all possible seven maximum number of rules.

$$\text{compositional similarity}_{A_1,A_2} := \Big(\sum_{r_i \in A_1, r_j \in A_2} r_i = r_j\Big) / |A|_{max} \tag{23}$$

Compositional spread is obtained by averaging the similarity over the entire population.

6.2.3 *Test of learning algorithm*

A series of simulations were run to test out the soundness of the learning algorithm. In these simulations, the game was played by two agents, one adopting the role of teacher, while the other was a learner. The learner had no predefined language, being completely new to the

number	cover	syntax	semantic	weight
R 21	S →	A·G·E	[circle, square, right, left, green, red]	1.0
R 9	E →	"y"	[green]	1.0
R 22	A →	"s"	[right]	1.0
R 19	G →	"s"	[square]	1.0
R 18	G →	"t"	[circle]	1.0
R 3	A →	"e"	[left]	1.0
R 15	E →	"n"	[red]	1.0
R 4	B →	"tn"	[circle, red]	1.0
R 5	B →	"sy"	[square, green]	1.0
R 17	F →	"st"	[circle, right]	1.0
R 10	F →	"et"	[circle, left]	1.0

Table 5: Maximally weighted rules induced by a learner in a two-agent teacher-learner game designed to test the soundness of the learning algorithm.

game, and always played the role of hearer. The learner always cooperated and tried to guess the meaning of the utterance until success. The teacher had a fully developed language. In fact, the teacher was agent number 1 in the simulation chosen as an example to discuss the compositional language developed by a population. The language is fully depicted in table 14 in appendix A.3. The teacher's maximally weighted grammar is shown in table 15 in the same appendix. The teacher's language was the result of a simulation of altruistic agents. The resulting language is discussed in more detail below, see 6.5. This test was repeated twenty times, each time with a different random seed. The number of interactions was set at 3000, although in all simulations the grammar was fixed within the first 200 interactions.

Table 5 depicts the maximally weighted rules of the language induced by the learner. All simulations ended with the same maximal rules, except two, in which rules R-17 and R-10 were not learned, and rules R-4 and R-5 were learned but not maximally weighted and never used. The maximal ternary and atomic rules are the same as the teacher's, as was expected. Consistency at the end of the game is 0.75, which is explained by the presence of synonyms in the atomic rules, with *right* and *square* sharing the expression "s". Compositional similarity, measured by the number of maximal atomic and compositional rules that the two grammars have in common, is 1.

The same batch of simulations were run with a language resulting from the interaction within a group of mutualistic agents interacting under high costs, $c_a = 0.95r$ and $c_c = 0.85c_a$. Mutualistic populations under these conditions develop poorly shared languages, although an agent's internal language may be refined. Indeed, such an agent was used as a teacher in a batch of twenty simulations, each of them with a different random seed. The teacher's maximally weighted rules are contained in table 6, while the learner's maximal grammar is shown in table 7.

Both agents use the same compositional rule, R-0 for the teacher and R-16 for the learner. However, this rule is not fully generalised, since it cannot be used to refer to red objects. The teacher will use holistic expressions for actions which include the meaning *red*, such as the two last rules included in its grammar. Although they are not maximally weighted, they have been included to illustrate how the teacher will communicate. Rule-59 is more effective, so the learner learns to use its rule R-25. Notice how the learner has included a binary rule, R-15, which applies to three meanings in two different semantic categories. Consistency in all twenty simulations is, however, high, reaching 0.75. In only three of the simulations did teacher and learner end up using the same compositional rule. Average similarity over twenty results was 0.35.

number	cover	syntax	semantic	weight
R 0	S →	E·A·G	[circle, square, right, left, green]	1.000000
R 50	H →	"goc"	[circle, left]	1.000000
R 18	G →	"y"	[red]	0.999331
R 20	H →	"hji"	[circle, right]	0.999061
R 19	G →	"c"	[green]	0.998374
R 22	S →	"bjg"	[circle, left, green]	0.998177
R 57	B →	"xy"	[circle, green]	0.995942
R 28	E →	"p"	[square]	0.993864
R 21	A →	"s"	[right]	0.982262
R 30	H →	"aky"	[square, left]	0.981557
R 31	A →	"g"	[left]	0.969975
R 59	S →	"pgmupcq"	[square, right, red]	0.596491
R 83	S→	"hocslsnlzp"	[square, right, red]	0.399304

Table 6: Teacher's maximally weighted rules. The teacher was chosen from a population of mutualistic agents that did not develop a fully shared common language.

number	cover	syntax	semantic	weight
R 16	S →	E·A·G	[circle, square, right, left, green]	1.0
R 15	H →	E·A	[square, right, left]	1.0
R 4	G →	"c"	[green]	1.0
R 14	A →	"s"	[right]	1.0
R 12	E →	"p"	[square]	1.0
R 18	E →	"c"	[circle]	1.0
R 13	A →	"g"	[left]	1.0
R 21	S →	"pxs"	[circle, right, red]	1.0
R 25	S →	"pgmupcq"	[square, right, red]	1.0
R 20	S →	"yaky"	[square, left, red]	1.0
R 1	S →	"yzj'	[circle, left, red]	1.0

Table 7: Learner's maximally weighted rules. The agent learns from a teacher belonging to a population of mutualistic agents that did not develop a fully shared common language.

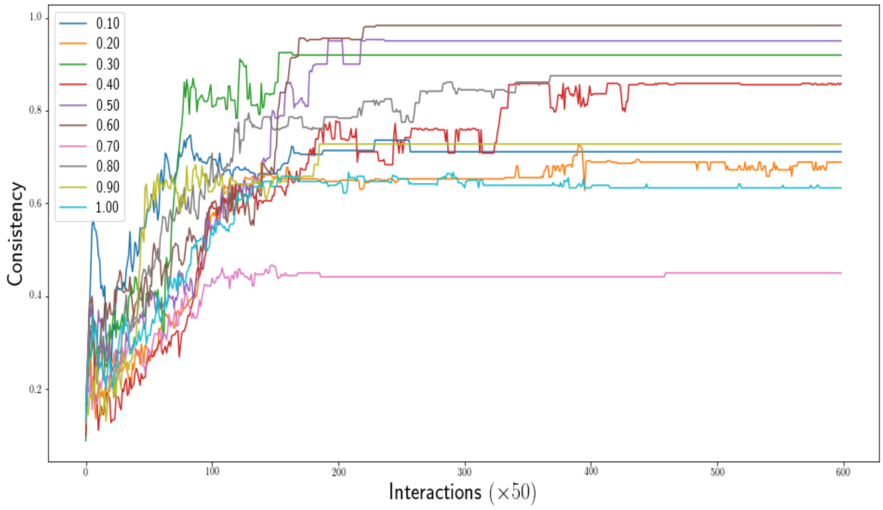


Figure 22: Linguistic consistency dynamics against interactions. Action cost is fixed $c_a = 0.15r$. Each curve traces the trajectory under a different coordination cost c_c.

6.3 EXPERIMENTAL STUDY I

6.3.1 *Simulation setup*

As in the study reported in section 4.4.1, this experiment sets up two independent groups of 10 agents. Again we run 20,000 simulations under each pair of values in the parameter space. Both the action and coordination costs are sampled at discrete intervals $\Delta = 0.1$, ranging $c_a = [0.01, 1.15]r$ and $c_c = [0.05, 1.15]c_a$.

6.3.2 *Results*

6.3.3 *System dynamics*

Figure 22 shows a common model behaviour, tracking the progress of a population's language consistency. Here, the action cost is fixed,

$c_c = 0.05r$. Each curve shows the consistency's trajectory under an increasing c_c. All trajectories display a similar pattern:

1. Consistency experiences a sharp initial increase. During the first interactions, agents invent and learn holistic rules, assigning an utterance to each action. At this stage agents are playing a simple *naming game* and their language will tend to converge, as shown in the experimental studies reported in sections 5.3 and 5.3.

2. As agents are presented with more utterances, the probability of finding similarities between strings increases. They can therefore begin to chunk expressions into rules and create compositional constructs. These rules are not shared initially by the rest of the agents, which causes a decrease in the consistency.

3. Agents receive utterances built from compositional rules. This provides them with the opportunity of chunking strings built using those rules, which allows them to internalise those rules themselves. This generally causes a subsequent increase in the accuracy.

4. As each agent reinforces some rules and decreases the weights in others, rules will tend to become fixated, causing the consistency in the group to stabilise.

The production of utterances by agents follows a distinct pattern throughout a simulation. This evolution is displayed in figures 23, and, as a detail of the first 800 interactions, 24. An initial short period in which agents create holistic rules is followed by a more extended one where agents employ holistic rules which they have already learned. Individuals partially invent utterances when they possess a rule with which they can encode part of the semantic content of the action, and make up the rest. It is used sparingly during the initial period of 200 interactions, alternating with more frequent holistic rules. After 600 interactions compositional rules begin to dominate

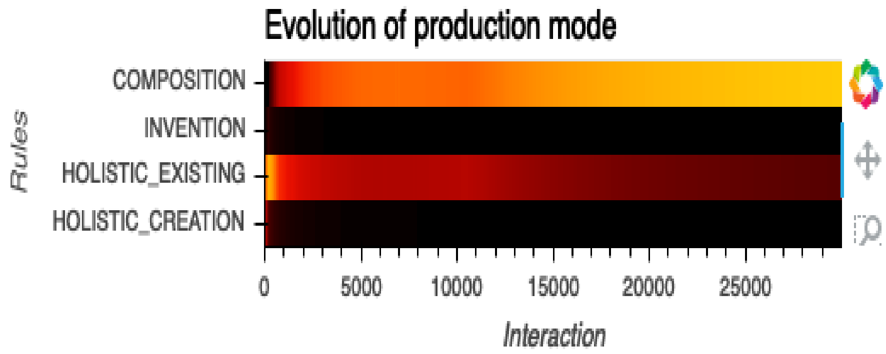


Figure 23: Evolution of mode of utterance production in a simulation. Agents tend to settle on compositional rules to create utterances after an initial period in which holistic rules are preferred. Notice how holistic expressions are used sporadically throughout the entire simulation.

over the rest of modes. However, holistic rules are employed sporadically throughout the entire simulation, showing how some agents have fixed a holistic expression to refer to an action.

6.3.4 *Linguistic stability*

The hypothesis is that an altruistic population would reach a higher level of linguistic consistency than a mutualistic population. To test this hypothesis, I have measured consistency in each simulation after 30,000 interactions; these measures constitute the population samples. Shapiro as well as D'Agostino and Pearson normality tests on the samples extracted from the 20 runs of each simulations support the hypothesis that the samples are normally distributed.

Figure 25 shows mean consistency over 20 runs for each value of a_c and c_c. Results for the altruistic group are quite uniform, displaying little variance; this is to be expected with agents that disregard cost and always cooperate. However, the mutualistic group is greatly affected by increasing costs: consistency is similar to the altruistic group for low action and coordination costs, but decreases as both parameters grow. The figure also shows that a low action cost can allow

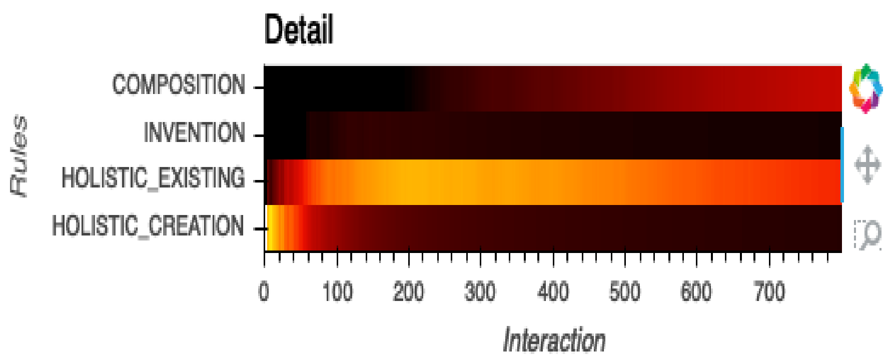


Figure 24: Detail of the initial 800 interactions of the simulation shown in figure 23. A short period dominated by rules that are being created by agents is followed by a greater use of already existing holistic rules. After 600 interactions compositional rules begin to dominate.

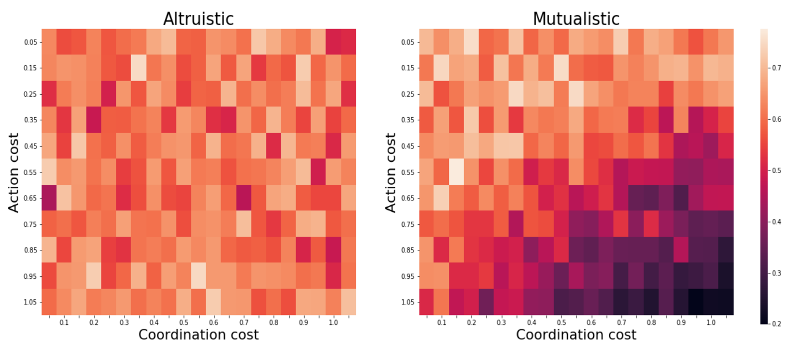


Figure 25: Mean consistency over 20 runs for altruistic and mutualistic populations respectively, for a range of values of c_a and c_c.

communication to become very costly, even greater than the cost of carrying out the action itself.

A Student's t-test was employed to test whether these differences are statistically significant – see Figure 26. p-values below 0.05 support the alternative to the null hypothesis that the samples obtained from each group come from the same distribution. Although p-values are low at many isolated spots in the heatmap, this can be assumed to be due to a multiple comparisons effect over our stochastic simulations; the consistently low area is where both cost parameters have high values, confirming that the mutualistic group

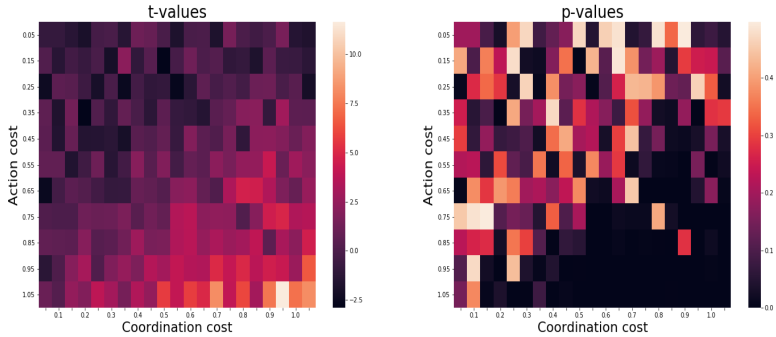


Figure 26: Student t-test results comparing final consistency from altruistic and mutualistic populations respectively, for a range of values of c_a and c_c.

shows reliably lower consistency in these conditions.

This result is strengthened by least squares linear regression taking c_a and c_c as independent variables and targeting consistency. Taking all twenty results of each parameter couple as samples, rather than their mean, and performing analysis on both altruistic and mutualistic populations, the results of the regression analysis are shown in table 8. The samples extracted from altruistic populations de not lend themselves to linear regression analysis, as can be deducted from the small coefficients which indicate a flat fit. Also, p-values > 0.05 as is the case for both action and coordination cost variables imply that there is no linear relation between the variables and the target. $R^2 = 0.0$ means that none of the variance in the samples is explained by the dependent variables.
Regression results are different for the mutualistic populations. Negative coefficients indicate an inverse relation between both variables and the target, the slope of the surface tilting downwards. p-values < 0.05 suggest that the hypothesis that there is a linear relation between costs and linguistic consistency cannot be rejected, and the $R^2 = 0.221$ value suggests that the linear fit covers some of the sample variance.
A stronger fit can be obtained by performing linear regression on

Table 8: Linear regression results for independent variables c_c and c_a target consistency

Consistency								
	Altruistic				Mutualistic			
	coefficient	t	P>|t|	R^2	coefficient	t	P>|t|	R^2
constant	0.6104	60.279	0.00		0.8117	95.219	0.000	
c_a	0.0103	0.869	0.385	0.000	-0.3058	-30.700	0.000	0.221
c_c	-0.0034	0.869	0.785		-0.2002	-19.240	0.000	

Table 9: Linear regression results for independent variables c_c and c_a target compositional spread

	Altruistic				Mutualistic			
	coefficient	t	P>|t|	R^2	coefficient	t	P>|t|	R^2
constant	0.8332	374.708	0.00		0.9346	181.638	0.000	
c_a	-0.0006	-0.329	0.742	0.000	-0.2860	-47.573	0.000	0.413
c_c	-0.0006	-0.329	0.742		-0.1974	-31.438	0.000	

the compositional spread. Results of this analysis is shown in table 9, having regressed over the compositional spread from all the simulations, rather than averaging per parameter value. While the altruistic samples show virtually no difference, other than an even flatter surface slope, the inverse relation between costs and spread is somewhat more pronounced than in the case of consistency. The slope is slightly steeper and R^2 is almost twice the value, indicating a better linear fit. Figure 27 shows the surface fit between costs and compositional spread. While the surface is almost entirely flat in the altruistic graph, with samples spread out almost everywhere in the space, the surface in the mutualistic graph slopes steeply towards the corner with greatest action and coordination costs.

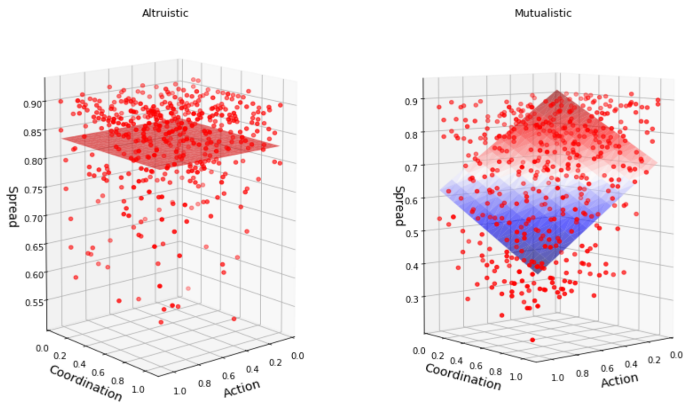


Figure 27: Linear regression surface showing the best fit between costs and compositional spread for both altruistic and mutualistic behaviour.

6.4 EXPERIMENTAL STUDY II

6.4.1 *Simulation setup*

I carried out an experimental study equivalent to the study reported in section 5.3, but in this case agents develop a language containing compositional rules. In this study one of the parameters was dropped, the initial number of altruistic agents, due to the computational demands required to calculate the linguistic consistency. The initial number of altruistic agents is fixed at half of the population, ensuring that both behaviours compete on a level field. Batches of 20 simulations were executed under all possible pairs of action and coordination costs. As in the holistic language study, the most interesting behaviour occurred with low c_a values; so c_a was at smaller intervals in that range. The discrete interval Δ for c_a is:

$$\Delta = \begin{cases} 0.01, & \text{for } 0 < c_a \le 0.10 \\ 0.10, & \text{for } 0.10 < c_a \le 1.15 \end{cases}$$

Population size is 30 agents. A maximum number of interactions was set at 50,000. All simulations were programmed and executed in Java 7. The average time for a simulation was around 4 to six hours. Because a great number of simulations were run (20 different values of action cost × 11 values of coordination cost × 15 to 20 simulations each), they were run on several servers, with one processor being applied to each simulation. A batch of simulations could run for 10 to 15 days. [1]

6.4.2 *Results*

6.4.2.1 *Population dynamics*

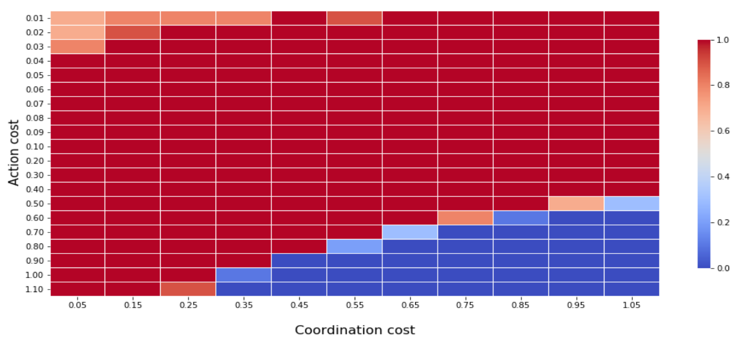
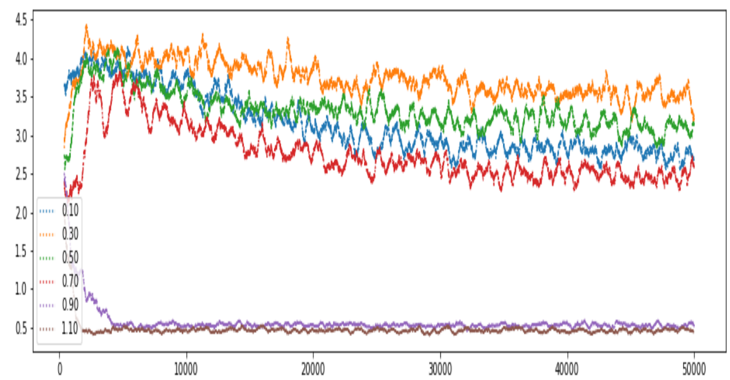


Figure 28: Percentage of simulations where altruism was the dominant behaviour under all parameter pairs, (c_a, c_c). Dark red indicates that all runs fixated at altruism.

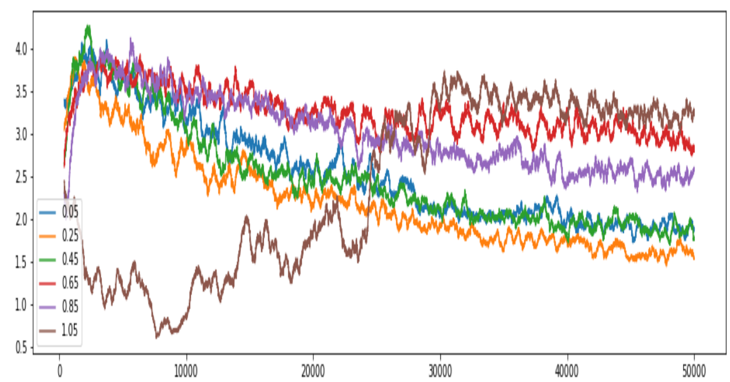
Figure 28 shows the fixation patterns of the population. Dark red cells represent parameter pairs in which altruism dominated. Results are consistent with those obtained in the holistic language study. Al-

1 The code to run simulations can be found at `https://github.com/mariano-mora/compositional_simulations`.

truistic agents enjoy a fitness advantage as long as the costs are not excessively high. However, it is remarkable that altruistic agents win out against mutualistic if the coordination cost is low, even when performing the action is greater than the reward.



(a) Evolution of the number of attempts under several values of c_a



(b) Evolution of the number of attempts under several values of c_c

Figure 29: Figure (a) shows the evolution of the number of attempts per interaction for increasing values of c_a. Here $c_c = 0.45c_a$ Figure (b) represents the number of attempts per interaction for increasing values of c_c. Here $c_a = 0.5r$

In figure 29a we see the evolution of the average number of attempts per interaction for increasing c_a values. The coordination cost is fixed at $c_c = 0.45c_a$. There is a very noticeable change after the action cost reaches $0.70r$. In figure 28 we can see that, for $c_c = 50$,

$c_a = 0.70r$ is the last action cost value under which the population fixates at altruism. Action cost values higher than $0.70r$ show an abrupt change in the behaviour of the agents, who are unwilling to engage in cooperative interactions. The average number of attempts per interaction is close to 0: agents almost never interact and there are no altruistic agents left.

6.4.2.2 *Language dynamics*

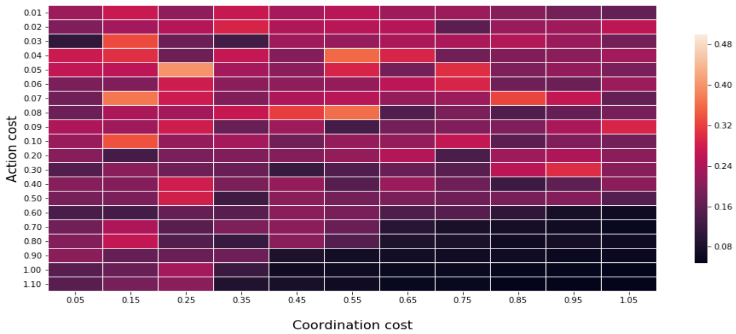


Figure 30: Mean final consistency after 50,000 interactions. Each cell represents the mean of 20 runs under a parameter pair, (c_a, c_c).

Figure 30 shows the mean consistency after 50,000 interactions for 20 runs under each pair of c_a and c_c values. The dynamics of the language coincides with the population dynamics. Notice that the mean consistency is never greater than 0.5.

The inverse relation between costs and compositional spread can be confirmed by regression analysis. As was the case with mutualistic populations in section 6.3.4, compositional spread slopes sharply towards the corner with the greatest action and coordination costs, a sign of an inverse linear relation. The sloping surface in figure 31 shows this inverse relation.

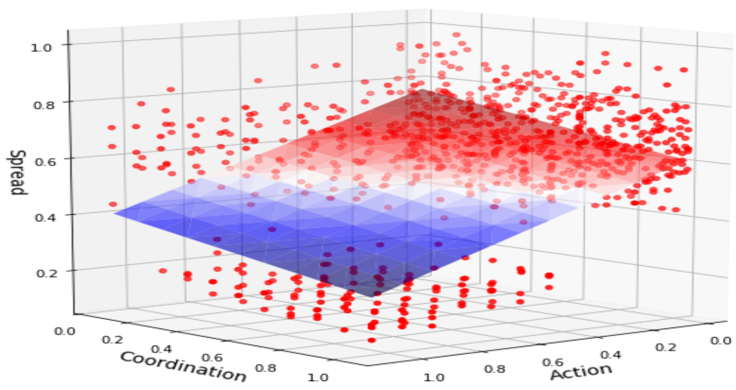


Figure 31: Multivariate linear regression surface between action and coordination costs as independent variables, and compositional spread as target.

6.5 ANALYSIS OF COMPOSITIONAL LANGUAGE

This section offers a closer look at the compositional language that emerges from the agents' interactions. A closer inspection unveils several characteristics of the language that are common to both types of studies. I begin by discussing them, before going deeper into results of both kinds of simulations. Table 14 in appendix A.3 displays a full common language from a randomly chosen simulation. In this case, a simulation of the interactions within a population of altruistic agents, with action cost $c_a = 0.55$ and coordination cost $c_c = 0.50$. It might prove a useful reference while discussing elements of the language.

6.5.1 *The compositional language*

This section takes a closer look at the compositional language created by agents interacting through the language game. It begins by discussing some aspects of the language shared by all agents in the population, as opposed to the agents' private language.

6.5.1.1 *The shared language*

A common language is understood to be made up of rules contained in every agent's internal grammar. A rule is shared by two agents if both have a rules with the same syntactic elements – be they terminal or non-terminal –, *and* the same semantic content. The weight associated to each rule may, and very often will, differ, since a rule's weight is determined by its success in an agent's interaction history.

The common language in appendix A.3 contains 94 rules. There are six types of rules, depending on their syntactic and semantic structure:

- **Compositional** rules. A rule's symbol is non-terminal. Its syntactic structure is made up of the composition of either three or two further rules.
  - A rule that prescribes the composition of three further rules must cover all three different semantic categories, *shape, colour* and *direction*. I refer to this type of rule as a *ternary* rule. The first three rules in table 14 in appendix A.3 are ternary rules.
  - A *binary* rule prescribes how to perform the composition of two daughter rules. It can cover two semantic categories, in which case I call it a *non-full binary*, or all three semantic categories, a *full binary*. In this last case, one of the daughter rules must have a syntactic category which covers two semantic categories. In the common language in appendix A.3 rule 4 is full-binary, while rule 8 is a non-full binary.

- **Terminal** rules. A rule whose symbol is a string. There are three possible semantic distinctions:
  - The rule covers all three semantic categories, in which case it is *holistic*, for example rule 21 in the common language.
  - The rule refers to two semantic categories. I call this a *compound* rule. A rule like this is the result of splitting holistic rules into common and non-common string and semantic parts. Very often the chunking procedure finds two rules with a common substring and a common semantic value. Two of the resulting new rules will then have two semantic values, forming a compound rule. An example is rule 34.
  - An *atomic* rule refers to a single category, and a single semantic value. Rule number 13 is an atomic rule. A language with fully atomic maximal elements possesses a compositional rule that dictates how to string together rule atomic terminals.

Figure 32 shows the distribution of types of rules in the common language as a percentage of the total number of rules.

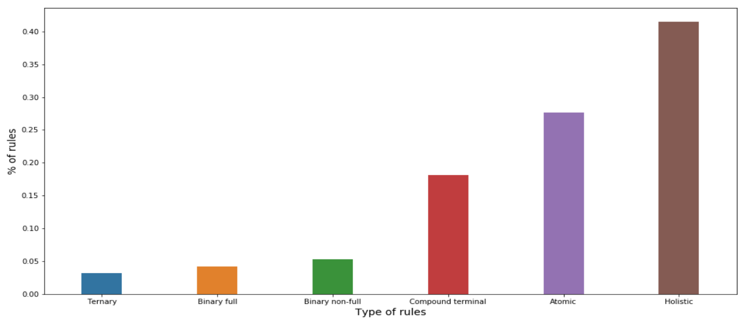


Figure 32: Distribution of types of rules in the common language of a group of altruistic agents, contained in appendix A.3.

Although all rules in the common language are shared by all agents in the group, agents may employ them very differently, making use of one or the other to encode utterances, or not at all. In this case, 50.6% of the rules of the shared language have actually been used by agents at least once, either to encode or to decode an utterance. Figure 33 shows the average use over the entire population of the common rules that have in fact been used.

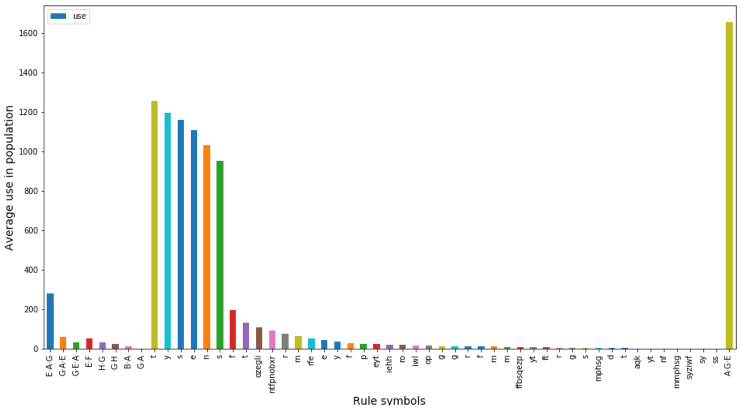


Figure 33: Average use over the entire population of rules contained in the common language.

An agent interacts with other agents an average 6000 times (30.000 total interactions between 10 agents who can interact in two different roles). However, the average usage for the most frequently used compositional rule in the common language is very low. The reason is that the most frequently used rule does not actually belong in the common language. An inspection of the maximally weighted rules in all ten agents' internal grammars depicted in table 15 in appendix A.3 shows that the maximally weighted compositional rule in every agents' grammar is:

R_0: S[s1+s2+s3] $\rightarrow$ A[s1=?], G[s2=?], E[s3=?]

which is fully generalised and atomised and applies to all six semantic values. This rule and its usage has been added as the last bar on the right in figure 33 – although, again, it does not belong *stricto sensu* to the common language – to show how commonly used it is in the population. However, agent 8's maximal compositional rule is somewhat different:

R_0: S[s1+s2+s3] $\rightarrow$ A[s1=left], G[s2=?], E[s3=?]

Agent 8 has not learned to generalise this rule so that it applies to both *left* and *right*, perhaps because the holistic utterance "ozegli" – meaning 'move the red square right' – is also very widespread in the population.

A notion of the how common a shared language is in a population can be obtained from table 10. It shows the most widely shared maximally weighted rule for all six different meanings in all twenty simulations of a population of altruistic agents interacting under $c_a = 0.5r$ and $c_c = 0.55c_c$. For each terminal utterance, the table shows how many of the ten agents have that rule as the maximally weighted for that semantic value. Included also is the spread of the most common compositional rule. The table suggests two things:

1. The language is shared to a high degree, with most words being shared by all or almost all the agents in almost every simulation. This includes the compositional rule as well. When all agents have all six atomic rules and a compositional rule in common, then their utterances are all the same.

2. The language need not be fully consistent, however. The abundance of synonyms means that many actions cannot be expressed in a *unique* way, and that many utterances have no unique interpretation. The table's last column contains the number of synonymous words that are maximal and commonly shared.

This suggests that a measure of the *spread* of common rules in a population would provide a more thorough understanding of how extended a language is.

6.5.1.2 *The internal language*

The size of an agent's internal grammar depends on its interaction history. An agent adds any new utterance it encounters to its internal grammar in the form of a holistic rule. This provides it with new opportunities to further expand its language by comparing the utterance and its meaning with rules already contained in the grammar.

Most of the rules in a grammar are seldom used when producing an utterance, but may help the agent decode another agent's utterance. Utterances are produced employing rules whose weights are greater than those of their competitors. An agent that interprets an utterance successfully reinforces the rule or rules employed, while decreasing the weight of competing rules. This reinforcement loop usually results in one rule being maximally weighted and being used almost exclusively.

An agent's internal language contains rules of the six types described above. Figure 34 shows the composition of the internal grammars of all ten agents in the population who share the common language of appendix A.3. The languages' average size is 426.7 rules. There are no duplicate rules: two rules that have the same syntax structure, for non-terminals, or string and the same semantic values have been merged. An agent may have at most six fully generalised ternary rules, since there are only six different orderings in which one can arrange three elements. Notice, however, how one agent, number 8, has more ternary rules. That is because an agent may have rules with three syntactic categories which are not fully generalised, the difference in semantic values between rules referring to different semantic categories.

The proportion of binary and holistic rules is greater than the proportion of atomic rules. This is because an agent incorporates any new utterance as a holistic rule. Any such utterance may not be part of its grammar either because it has been composed using rules that the agent does not possess, or because it has been partially decoded, which means that part of the utterance is not known to the agent. Adding the holistic rule to its grammar allows it to learn from it, comparing to rules it already knows and chunking parts of the utterance. Chunking an utterance produces three rules, one with the common parts and two with the non-common ones. It is twice as likely that the common semantic content of a holistic rule is made up of one value, rather than two, which means that two of the new three rules will be binary, while one is atomic. Hence the disparity in the number of binary and atomic rules. Further chunking of the binary rules can produce three more rules, in this case all three being atomic.

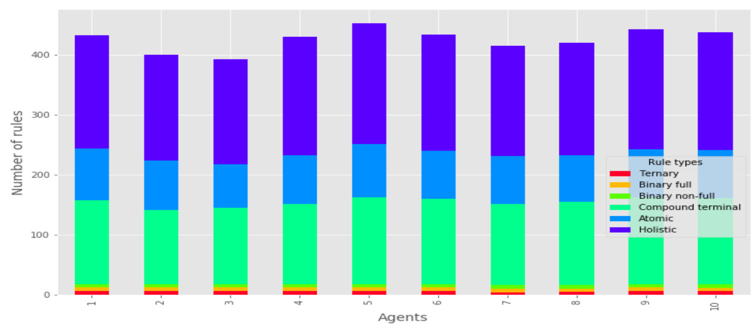


Figure 34: Types of rules in the internal languages of a population of ten altruistic agents.

Inspecting the rules that an agent has actually used, either to encode or decode an utterance, presents a slightly different picture. The number of atomic rules grows as agents chunk higher order rules further and use them to compose and interpret utterances. Figure 35 shows the proportions in which different types of rules have been used by the agents, a), and the number of rules of each type that are maximally weighted, b). An agent typically uses up to six or more ternary rules, but will tend to maximise one. A developed language consists in this case of one fully generalised ternary rule and six atomic rules, one for each possible meaning. Holistic rules will be a residue of the initial stages of language development, where all communication is holistic and holistic rules are used and reinforced.

An agent reinforces successful rules and decreases the weight of competing rules. Competing rules are of the same type: an agent will decrease the weight of a rule which has the same syntactic structure and semantic content as the one which has proved to be successful. Once a rule has established a lead over its competitors it will be very difficult for another rule to displace it. Although new rules are cre-

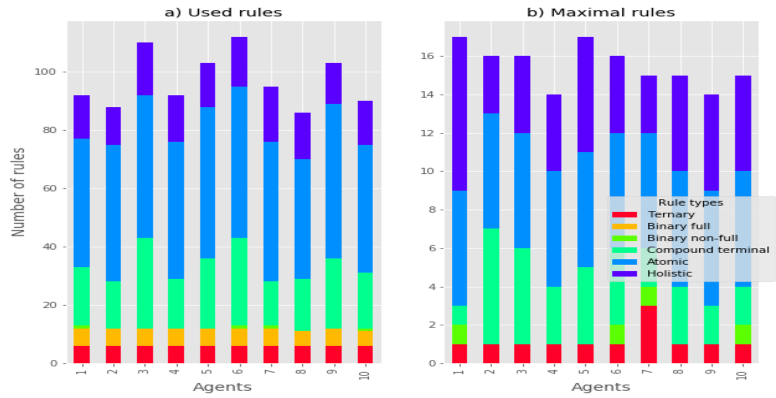


Figure 35: Figure a) shows the types of rules that have been used by agents in a population of altruistic individuals. b) shows the number of maximally weighted rules per rule type. The dimensions of the y-axis in both figures are very different, the size of a used grammar averaging one hundred rules, while each agent has an average of 15 rules. The dimensions are displayed in this way to facilitate viewing.

ated during an agent's entire history, it is almost impossible that a new rule takes over the top position.

Figure 36 shows the average number of rules for all six atomic and eight holistic meanings in the population of appendix A.3. Highlighted in red is the average order among all competing rules in which the maximal rule was created. A rule added to a language that already contains four (or less) rules with the same structure and the same semantic value will not end up prevailing in the population.

6.5.2 *Two groups case*

Because altruistic agents cooperate regardless of the cost, all the linguistic elements discussed in the previous section remain by and large unaffected by changes in the costs of coordinating and carrying out joint actions. The language of a group of mutualistic agents, however, is very much affected by how costly it is for the agents to

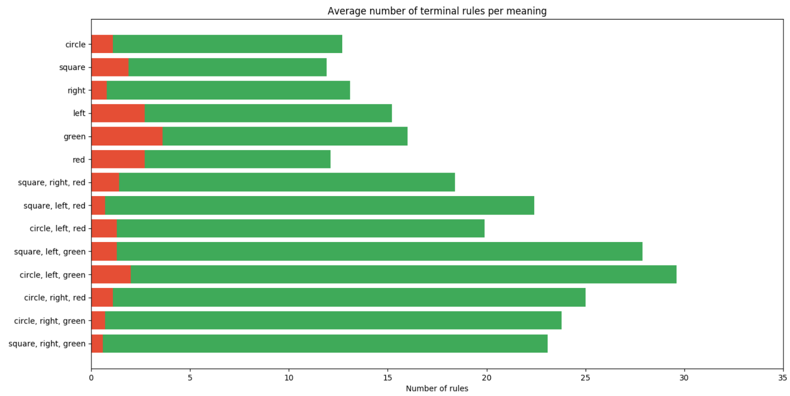


Figure 36: Average number of rules per atomic and holistic meanings. Shown in red is the average order of creation of the rule that ends up being maximally weighted.

cooperate. High coordination and action costs reduce the number of interactions, and this the chances for agents to learn from each other, so much so that there may be no rule that is shared by the entire population.

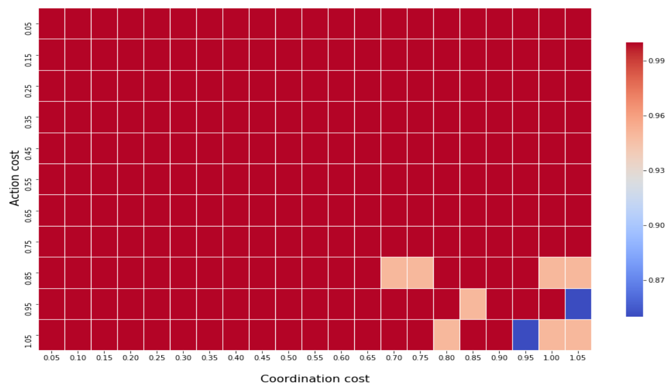


Figure 37: Percentage of simulations in which the populations developed a shared language. Twenty simulations were run for every pair of values c_a and c_c.

Simulation	circle word	count	square word	count	right word	count	left word	count	green word	count	red word	count	compositional word	count	synonyms
0	"y"	9.0	"k"	9.0	"oy"	5.0	"w"	9.0	"r"	10.0	"p"	9.0	E·A·G	10.0	0
1	"s"	10.0	"u"	9.0	"q"	10.0	"d"	9.0	"q"	10.0	"g"	9.0	A·G·E	10.0	2
2	"m"	10.0	"z"	10.0	"p"	10.0	"i"	10.0	"f"	10.0	"y"	10.0	G·E·A	10.0	0
3	"yihjca"	6.0	"f"	10.0	"f"	10.0	"q"	10.0	"j"	10.0	"p"	7.0	E·G·A	10.0	2
4	"z"	7.0	"x"	4.0	"x"	9.0	"y"	6.0	"x"	10.0	"z"	8.0	A·E·G	7.0	4
5	"q"	10.0	"a"	10.0	"t"	10.0	"z"	10.0	"y"	10.0	"b"	10.0	A·G·E	10.0	0
6	"l"	10.0	"t"	10.0	"m"	10.0	"t"	10.0	"t"	10.0	"l"	10.0	A·G·E	10.0	3
7	"m"	10.0	"r"	10.0	"r"	10.0	"h"	10.0	"a"	10.0	"r"	10.0	A·G·E	10.0	3
8	"t"	10.0	"s"	10.0	"s"	9.0	"e"	10.0	"y"	10.0	"n"	10.0	A·G·E	10.0	2
9	"x"	10.0	"k"	10.0	"map"	7.0	"i"	6.0	"k"	10.0	"a"	6.0	A·G·E	2.0	2
10	"v"	10.0	"x"	10.0	"w"	10.0	"v"	10.0	"l"	10.0	"c"	10.0	G·E·A	10.0	2
11	"z"	10.0	"v"	10.0	"m"	10.0	"sf"	9.0	"y"	10.0	"o"	9.0	A·E·G	10.0	0
12	"c"	9.0	"g"	10.0	"q"	10.0	"k"	10.0	"a"	10.0	"o"	10.0	E·A·G	10.0	0
13	"a"	7.0	"a"	6.0	"w"	5.0	"c"	5.0	"r"	4.0	"r"	7.0	E·G·A	4.0	2
14	"x"	10.0	"r"	10.0	"i"	10.0	"l"	10.0	"v"	10.0	"d"	10.0	A·G·E	10.0	0
15	"n"	10.0	"c"	10.0	"u"	10.0	"n"	10.0	"m"	10.0	"k"	8.0	G·A·E	9.0	2
16	"c"	10.0	"q"	5.0	"q"	5.0	"l"	8.0	"k"	8.0	"l"	10.0	A·E·G	8.0	2
17	"i"	6.0	"z"	9.0	"z"	8.0	"m"	9.0	"y"	10.0	"z"	10.0	E·A·G	2.0	3
18	"e"	10.0	"u"	10.0	"gerlfwq"	10.0	"u"	10.0	"c"	10.0	"e"	10.0	A·E·G	7.0	2
19	"a"	6.0	"p"	8.0	"a"	8.0	"i"	9.0	"b"	10.0	"a"	5.0	E·G·A	9.0	3

Table 10: Most commonly shared rules in all twenty simulations of a population of 10 altruistic agents with $c_a = 0.50$ and $c_c = 0.55$. The last column shows the number of synonyms.

Figure 37 shows the percentage of all twenty simulations per parameter pair, c_a, c_c where the population developed a common language. It is rare for a population not to share at least one rule. The size of the common language drops drastically as the costs increase above 60% of the reward and the coordination cost rises to more than a third of the action cost. Rules shared and actually used by the agents, as well as maximally weighted rules, also show a steep decline as the costs increase. Figure 38 show the average size of common languages for each pair of costs reached by populations of mutualistic agents. A common language in a population of mostly cooperating agents, i.e. when costs are so low that the probability of affecting an agent's decision to cooperate is very small, will typically consist of ninety rules, as shown in the first graph. The number of those rules that have actually been used by agents is shown to average 24 when the costs are very low, while the number of shared rules that are maximally weighted by agents is half that. When costs increase to the maximum, which means that cooperating is actually more costly than the potential reward, most populations share no maximally weighted rules, each agent having its own internal grammar.

Compositional spread offers a measure of similarity between the internal languages of the members of a population (see section 6.2.2). Individuals have a common compositional language if they share the compositional rule as well as all the words for the six possible different meanings, and all are maximally weighted. If the compositional rule is fully generalised, i.e., agents apply it to all six meanings, then all possible utterances are produced by employing this set of rules.

As is the case with other elements, the spread of the language is not affected by varying costs in populations of altruistic agents. Mutualistic agents, however, do not develop a common compositional language that is shared by the entire or a great part of the population when costs increase with respect to the reward obtained from cooperating. Figure 39 shows the compositional spread in populations of

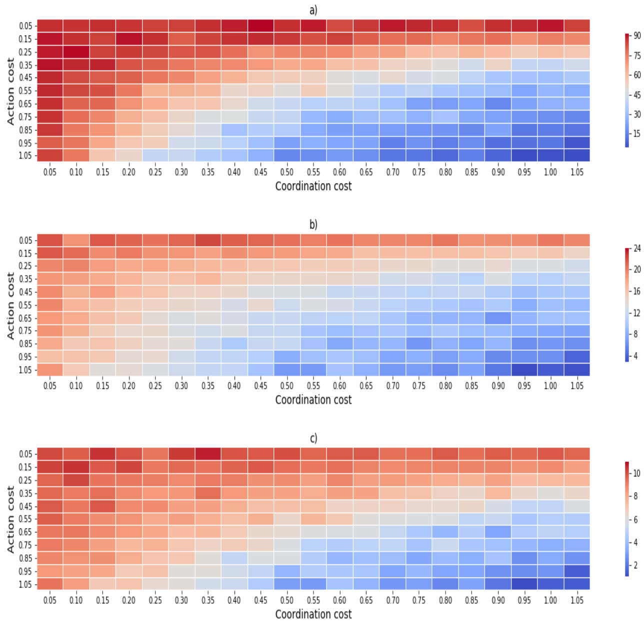


Figure 38: Sizes of languages in mutualistic populations under a range of pairs of cost values, averaged over the populations of twenty simulations.. a) displays the average size of the language consisting of rules shared by all agents. b) displays the average number of those rules which have been effectively used by agents, while c) shows the average number of common rules that are maximally weighted by the individuals in the population.

altruistic and mutualistic agents over all possible pairs of action and coordination costs. Spread results have been averaged over all twenty simulations. The graphic shows very clearly the effect of increasing costs on the level of commonality of the language shared by the population. Consistently with previous results, one can notice a sharp contrast when $c_a > 0.55r$ and $c_c > 0.45c_a$. This can also be verified in figures 40 and 41, which show details of the average spread of some semantic values and of the compositional rule respectively.

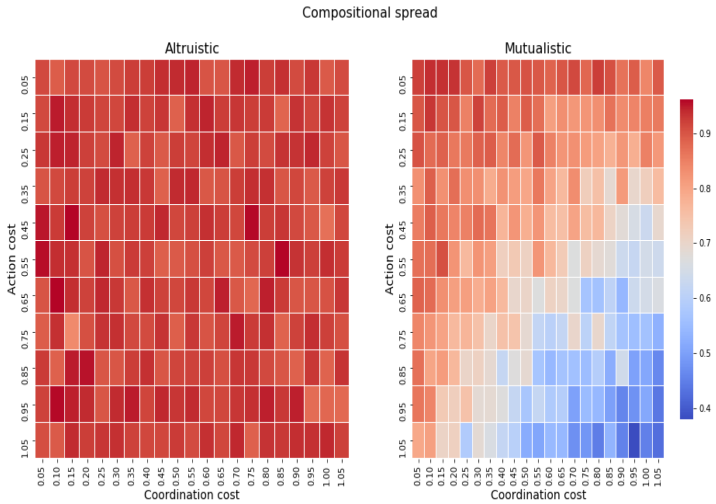


Figure 39: Average compositional spread for altruistic and mutualistic populations for pairs of cost values. Results are averaged over all twenty simulations for each pair.

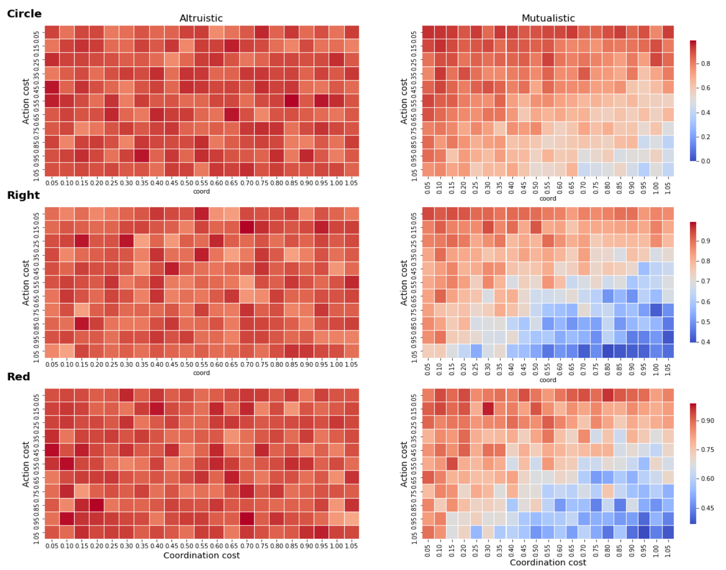


Figure 40: Detail of average spread of the atomic rules for ’circle’, ’right’ and ’red’.

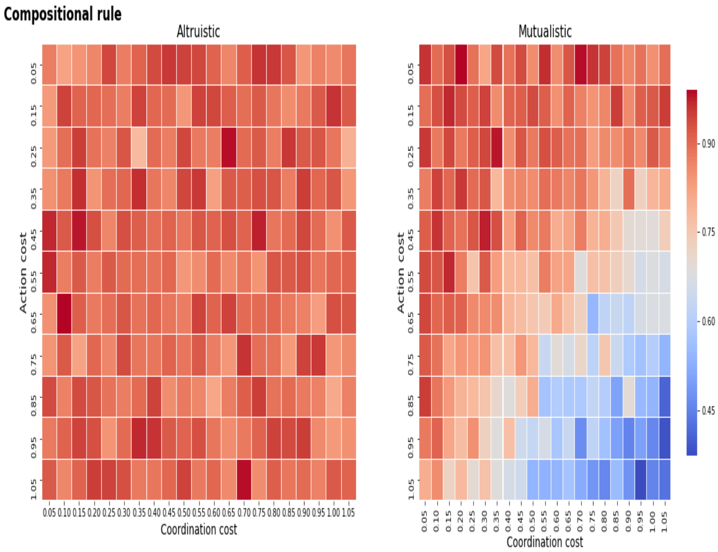


Figure 41: Detail of average spread of the compositional rule

6.5.3 *Single mixed group*

The results discussed in section 6.4.2.1 show that an altruistic strategy is quite resistant to increases in environmental and communication costs. A population interacting in an environment in which carrying out an action costs 60% of the reward and coordinating the action is also 60% of the action cost will still favour altruistic behaviour over mutualistic. The sturdiness of the cooperating behaviour is carried across to the resulting language: populations where altruistic behaviour dominates develop a language which is widely spread and compositionally refined.

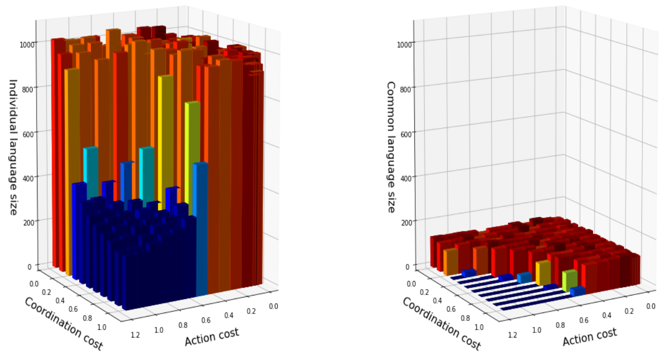


Figure 42: Side by side of images of the average size of internal and common languages.

Figure 42 displays side-by-side images of the average size of internal and common languages. Agents develop very large internal grammars, as is to be expected from the greater size of the population – 30 agents – compared to the ten agents which made up the populations of the two-group experiments. Agent must acquire many more rules, especially holistic rules, as a result of an increase of the number of different agents they encounter throughout their interaction history. An action cost of 55% of the reward together with a high coordination cost ($c_c > c_a$) causes an abrupt drop in the sizes, particularly that of the common language. The area of the graph towards the corner with the greatest costs shows no or almost none common language, with most populations not having developed a single rule that is shared by all agents. The transition is abrupt, as seen by the small number of squares that are not either a shade of red or completely blue. Again, the size of the population decreases the probability of all individuals learning the same rule unless that rule has enough time and opportunities to establish itself.

The number of rules in the common language that have actually been used by individuals is similarly distributed, with abrupt decreases and drops to zero when $c_a > 0.55r$ and $c_c > 0.8c_a$. This is shown in figure 43, where the left graph displays the average number of rules in the common language which have been used by all agents. The right graph shows the number of common rules that are maximally weighted by all agents. The area of the parameter square occupied by mostly red rectangles presents an almost flat surface averaging 7 maximal rules, indicating a high level of shared atomicity, most agents sharing the ternary and six atomic rules. This corresponds to a high level of compositional spread.

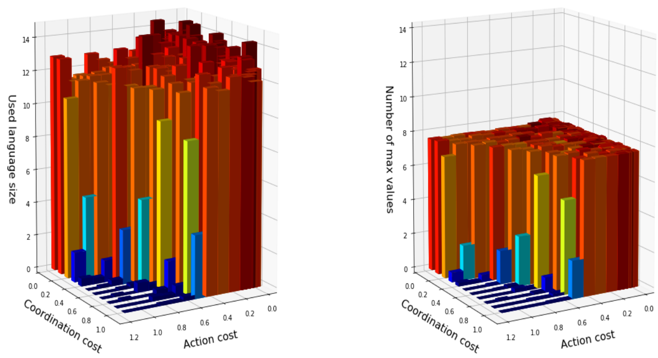


Figure 43: Average number of rules in the common language which have been used by agents, left, and average number of maximally weighted common rules, right.

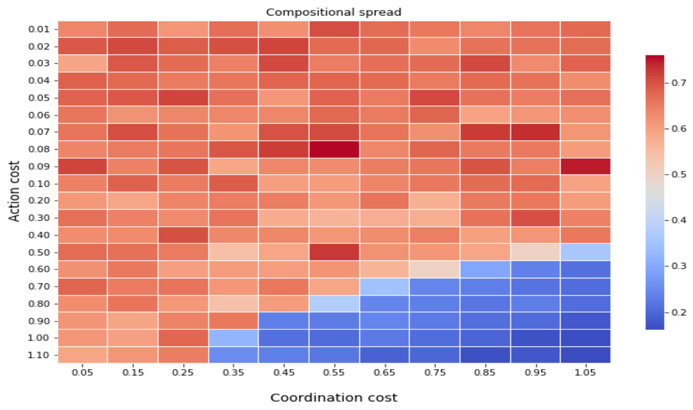


Figure 44: Average compositional spread.

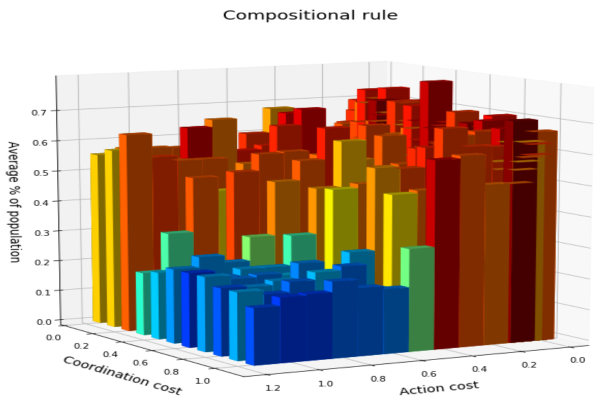


Figure 45: Average spread of compositional rule.

Figure 44 shows the compositional spread averaged over all simulations. A more detailed perspective can be gained from the average spread of the compositional rule, figure 45, as well as from the spread of the atomic rules for all six semantic values, shown in figure 46.

6.6 SUMMARY

This chapter has reported on two studies that test the conditions under which cooperating behaviour affects the emergence of a compositional language. Agents are provided with a number of mechanisms through which they can induce a probabilistic grammar from utterances they receive from other agents. This grammar consists of a set of rules that admit to semantic content. Agents create syntactic categories as they induce their internal grammar, gluing together semantic categories. Agents can *incorporate* new expressions into their grammar in the form of holistic rules; they can *chunk* expressions when they identify common substrings in them; and they can *generalise* to more comprehensive rules that can contain more general semantic content. Agents use these rules to encode utterances. They can invent new holistic expressions; or exploit rules that contain parts of the semantic content required; or concatenate terminal string into compositional expressions. A shared compositional language emerges when agents reinforce successful rules, thus increasing their future use and increase the probability that they spread throughout the population.

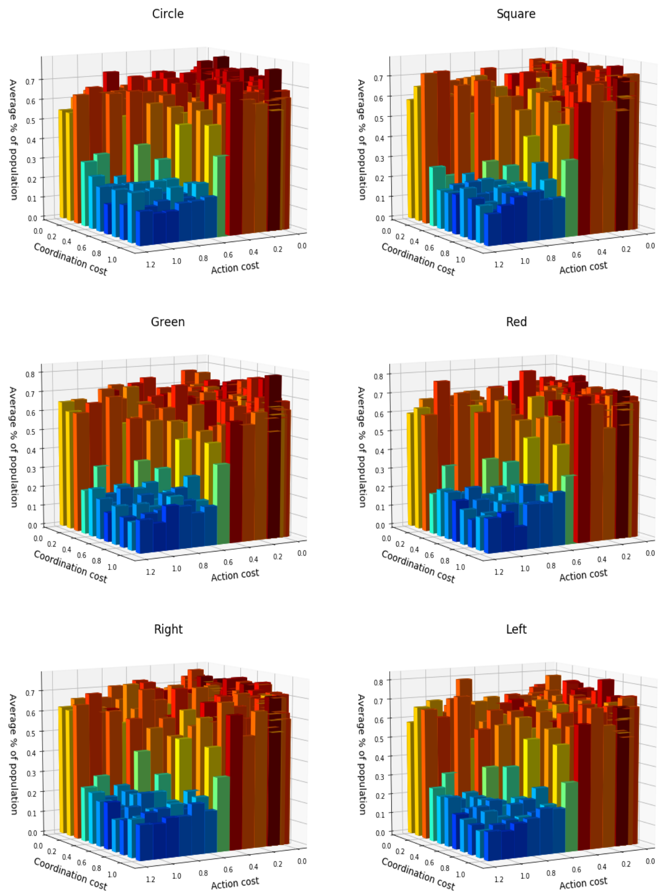


Figure 46: Average spread of atomic rules for all six semantic values.

7

CONCLUSION AND FUTURE WORK

In this final chapter I make the case that the research presented in this thesis effectively contributes to scientific knowledge. I examine the original contributions of the research, how it fills some gaps that had not been considered. The main findings are the results of the experiments, which I recapitulate and review, before considering some of the new lines of questioning that should be pursued in future experiments.

7.1 CONTRIBUTION TO KNOWLEDGE

This work belongs to an expanding body of work on computer simulations of language evolution. It relies heavily on work by others (Steels, 1997a; Hurford, 1989; Kirby, 2000; Vogt, 2005) and implements methods that have been tested in areas such as evolutionary biology, social and cultural evolution, artificial intelligence, robotics, etc. One of the strongest contributions of the research is that it selects elements from different areas of knowledge and combines them to fill gaps in the main field of computational simulations of language evolution. Some of these elements are:

- The interactions between agents are embedded within a protocol in which communication has *consequences for the agents* themselves, not only their language.
- Modelling the interaction in terms of *decisions over costs* allows us to study the evolution of the language as a result of adaptation to selective pressures. This adaptation takes place as two learning processes: behavioural and linguistic.

- Separating *two different categories of costs*, environmental and linguistic, makes it easier to analyse the contributions of both adaptation mechanisms.

- The *game model* provides a way of quantifying the impact of altruistic behaviour on the evolution of language against that of mutualistic behaviour, making it possible to directly compare two opposite cooperation strategies.

The main contribution to knowledge of this thesis are the results of the experiments, which I briefly summarise in the next section (see 7.2). Linguistic evolution follows distinctively different paths depending on the cooperating behaviour of the population. That path is also determined by the environmental and linguistic costs. Moreover, given certain limit cost values, there will be no language evolution at all. The population itself will evolve towards one behavioural trait or another depending on the costs, and that evolution will be determined not only by environmental costs, but also by the cost of communicating.

A final contribution to the field is the methodology employed, which introduces several elements that had so far been ignored in most of the research on computational simulations. The *interaction protocol* itself grants the agents the possibility of reconsidering their willingness to interact. By extending the interaction into several different costly decisions we can evaluate the cost-effect of a progressively more accurate and common language. A language that allows agents to communicate quickly can thus have an effect in the fitness of the agents themselves. This effect could have been expressed as a variable that decreases proportionately as the number of successful interactions increases, but results are a better representation of the evolution of the language if this variable is determined directly by the history of interactions within the population.

Another methodological contribution is the *simulation process*, which studies the behaviour of the language in the population over the whole range of possible couples or triplets of values. Under such a parameterisation the simulations inform us not only of differences in the evolutionary paths, but *under which conditions*, and how dramatically, those paths begin to differ.

Finally, a *statistical approach* to the experiments validates the conclusions that can be extracted from the analysis of the simulations. Very often, computational simulations are not run in batches or repeated enough times to account for outliers, stochastic variance or simply statistical errors.

7.2 DISCUSSION OF RESULTS

7.2.1 *Holistic language experiments*

Chapter 5 described two studies in which populations of agents developed a holistic language. Agents interacting in two independent populations, which I have termed Type I study, showed that a population of altruistic agents will converge to a common language faster, i.e. it will require fewer interactions, than a population of mutualistic agents *if* environmental and linguistic costs are sufficiently high. The difference between populations becomes noticeable as soon as the cost of carrying out the action is 40% of the potential reward that agents obtain from the action. Moreover, if the costs of communicating is greater than 45% of the cost of performing the action, then the difference between an altruistic and a mutualistic population becomes significant as soon as the action cost is 20% of the reward. It is interesting to notice that the convergence to a common language behaves differently in both populations even if communication costs are very low. Altruistic agents will reach convergence faster as soon as $c_c > 0.1c_a$ and $c_a > 0.4r$. Mutualistic populations do not reach a common language if the costs are contained within the area defined by the limits $(c_a > 0.45r, c_c = c_a) \cup (c_a > r, c_c > 0.4c_a)$, as shown in figure 18.

Low communication costs play a more significant role to the fitness of agents in a population in which they must interact with agents of a different strategy to their own. Altruistic behaviour spreads throughout the entire population if the cost of communicating is less than 25% of the action cost, even if the cost of performing the action is 75% of the reward. Figure 19a shows how altruistic behaviour is predominant in the area under the parameter plane delimited by $(c_a < 1.1r, c_c < 0.1c_a) \cup (c_a < 0.2r, c_c < c_a)$. Costs above this plane favour mutualistic behaviour, since altruistic agents incur in too high a cost helping others, and this cost is not compensated by other agents helping them. If both costs are low, however, either strategy can dominate, as seen in figure 20. When $c_a < 0.05$ the dominant strategy depends on the initial proportions of both strategies. If the population initially contains more than 20% of altruistic agents, then altruism will end up dominating the population.

A mixed population can develop a common language regardless of which strategy ends up dominating if the costs are within certain limits. Figure 19b shows that convergence to a common language is strongly linked to altruistic behaviour, so much so that parameter triples that lead to a fixation at mutualistic behaviour almost always imply that the population will not reach a common language shared by the entire population. This does not apply to very low values of action, communication costs and initial proportion of altruistic agents, where, as mentioned in the previous paragraph, the mutualistic strategy dominates over altruism, and the population still develops a common language.

7.2.2 *Compositional language experiments*

Results from the Type I study in independent populations of agents that use a compositional language support the hypothesis that a purely altruistic population would reach a greater level of linguistic consistency than a purely mutualistic one. In other words, a greater fraction of the population shares a greater fraction of the language. As shown in figure 25, this result stands for $c_a > 0.35r$ when $c_c > 0.8c_a$ in general. This is corroborated by an analysis of compositional spread, which provides a measure of the percentage of the population that shares common rules for the composition of atomic rules, which are terminal expressions referring to single meanings, or words.

A Yype II study mirrored the results from the analogous study on holistic languages. In a mixed population, altruistic behaviour is a dominant strategy for a large part of the parameter space. Mutualistic behaviour dominates for a range of values determined by $c_a > 0.6r$ and $c_c > 0.6c_a$, as shown in figure 28. Interestingly, either strategy can dominate if the costs are very low, $c_a < 0.03r$ and $c_c < 0.25c_a$, though altruism has a slight edge in that range as well. Development of a common language follows a similar pattern, showing greater consistency and spread in populations where altruism is the dominant strategy, while failing to develop a single rule that is shared by all agents when the costs increase above $c_a > 0.8r$ and $c_c > 0.6c_a$, see figure 30.

An analysis of the compositional language that emerges from the interaction shows that compositional rules concatenating atomic words are common in populations in which agents are willing to interact enough. Holistic rules are still shared by agents, and used sporadically. A rule cannot end up dominating over all competing rules if it is created too late, when there are already more than four rules with the same semantic content.

7.3 CONCLUSION

The results obtained in all four studies support the notion that altruistic behaviour played a decisive role in the evolution of language. The studies that form the bulk of this thesis were designed so that they could be applied to different stages in the evolution of language. Each study has attempted to verify and extend the results obtained in the previous one. Evolution does not leap.

Environmental and linguistic costs represent a pressure under which altruistic behaviour is a selective advantage: both cooperation strategies are similar when both types of cost are low, a situation in which mutualistic agents are not discouraged from helping others and being in turn helped by others. Under such conditions, both types of helping behaviours can lead to the emergence of a common language. An increase in costs, i.e. an increase in the harshness of environmental conditional that reduces the difference between the cost of carrying out an action and the reward obtained from it, as well as an increase in the cost of communicating, lead to altruistic behaviour being the strategy that allows the emergence of language, whereas mutualistic populations do not develop a common language under harsher conditions. Altruistic behaviour also allows populations to develop a language when communicating is very costly, for instance when the encoding and decoding of utterances requires a high cognitive effort or communicative mistakes can be very costly to the individuals. The emergence of a holistic language requires a radically different set of cognitive capacities than does the emergence of compositional structures. Also, the social and environmental pressures that facilitated the evolution of holistic languages cannot be compared to the ones that brought about the evolution of compositional structures. This work, however, shows that altruism has played an important part in both. Altruistic populations, either in a pure or a mixed population, develop a more sophisticated shared compositional language than mutualistic populations.

7.4 FUTURE WORK

The cooperation model introduced in this thesis can be used to investigate how other social mechanisms may have affected the evolution of language, and *vice versa*. Other forms of cooperation have been proposed as requirements for the evolution, not only of language, but also of very diverse social constructs.

- **The effect of memory** In all four studies presented here, agents had a memory window of one. The memory window determines the number of interactions that mutualistic agents take into account when they compute the expected cost (see section 4.1.1, equation 14). The expected cost directly determines the probability of engaging in the interaction. Considering only one previous interaction causes the agent's behaviour to swing from one interaction to the next (Baek et al., 2016; Hilbe et al., 2017). A mutualistic agent who has paid a heavy price in one interaction (either because its partner defected or because the interaction took a large number of attempts) will decide not to cooperate in the next one, or defect after only one attempt. This resets its memory to a low value, and gives it a poor understanding of the real costs. This means that it is willing to help at the next interaction, which in turn causes it to defect in the subsequent one. The agent could eventually fall into a strategy of alternating helping and defecting decisions, depending on the probability of alternating the role of speaker and listener. Although this is a clever strategy, especially when the costs are shared equally, it is debatable whether this is a good representation of a self-interest seeking agent. Averaging the costs over a longer window of interactions would provide the agent with a much more realistic notion of the costs.

- **Direct and indirect reciprocity**. The interaction model can easily be adapted to investigate the effect of both mechanisms on the evolution of language. Nowak and Sigmund (2005) suggested that indirect reciprocity may have been directly involved in the evolution of language as a way to convey information to fellow cooperators about unreliable cheaters. Wang and Steels (2008) simulated the linguistic emergence of a lexicon among agents who were willing to punish non-cooperators. It would be very interesting to test the validity of those mechanism in a model that allows the emergence of language to be a fitness advantage.

- **The effect of new generations, applying the ILM**. It seems reasonable to believe that the positive effect of altruism on the evolution of language would be reinforced with the transmission of language to a generation of learners. Since one generation of altruists is capable of reaching significant linguistic consistency, the rules of the language would already be shared by a large enough fraction of the population that new generations would be exposed to expressions produced from a relatively small number of rules. One question that should be addressed is the relation between altruism and the size of the linguistic data that a learner is exposed to, the linguistic *bottleneck*.

- **Do mutualistic agents benefit from the common language?** This question would have to be addressed from two angles. First, the obvious way in which mutualistic agents would benefit from interacting with altruistic agents is by enjoying their help when they require it, i.e when they play the role of speakers, while not helping when it is their turn to be the listener, the *free rider* problem. However, because they do not cooperate as listeners, they do not have a chance to learn the shared language. This means that their interactions as speaker will always be particularly costly, because even altruistic agents with a good knowledge of the common language will not understand them. Investigating this possibility would not require measuring the individual benefit to each agent of learning to communicate, but rather the average communication gain for each cooperation strategy, i.e the average number of attempts per interaction for each strategy and the fitness benefits it provides.

A

APPENDIX

A.1 NORMALITY TESTS

Table 11 shows the results of two different normality tests carried out on the samples obtained from running fifty simulations at each learning rate value on both populations. Each sample represents the number of interactions required to reach full linguistic overall consistency for that particular simulation run. Although some p-values are above the 5% α threshold, no batch is normally distributed on both populations at any learning rate.

The same can be said of normality tests applied to simulation runs for both populations under with different action costs. Table 12 displays results of two different normality tests on samples obtained from fifty runs of simulations for each value of the action cost. Low p-values do not allow us to infer that the samples are uniformly distributed.

A.2 MANN-WHITNEY NON-PARAMETRIC TEST

The Mann-Whitney U test is a non-parametric method to compare two independent samples (Corder and Foreman, 2014). The two samples are combined and rank ordered together. A random rank order would mean that the two samples are not different, while a cluster of one sample's values would indicate a difference between them. The U statistic is determined through the following equation:

$$U_i = n_1 n_2 + \frac{n_i(n_i+1)}{2} - \sum R_i \tag{24}$$

	Shapiro-Wilk		D'agostino-Pearson	
	altruistic	mutualistic	altruistic	mutualistic
Learning rate	*p*-values	*p*-values	*p*-values	*p*-values
0.10	6.35e-02	0.177	2.24e-02	0.360
0.20	3.07e-09	0.001	1.35e-14	0.016
0.30	3.79e-05	0.000	3.55e-08	0.002
0.40	4.24e-10	0.000	9.89e-17	0.010
0.50	5.64e-11	0.044	2.34e-16	0.143
0.60	2.54e-01	0.067	2.67e-01	0.064
0.70	1.86e-13	0.001	1.78e-22	0.067
0.80	2.98e-03	0.033	6.25e-04	0.009
0.90	5.56e-12	0.000	6.00e-21	0.000
1.00	3.34e-02	0.286	3.28e-03	0.219
1.10	2.43e-06	0.034	3.02e-07	0.002
1.20	4.14e-04	0.097	3.99e-05	0.017

Table 11: *p*-values from Shapiro-Wilk and D'Agostino-Pearson's normality tests on run results for various learning rates. p-values < 0.05 on both types of population allow us to reject the null hypothesis that the samples are uniformly distributed. Differences in the distributions of the two populations can, however, be tested using non-parametric methods.

		Altruistic		Mutualistic				Altruistic		Mutualistic	
action	**coord**	stat	p-values	stat	p-values	**action**	**coord**	stat	p-values	stat	p-values
0.10	**0.05**	0.95	0.17	0.96	0.26	**0.50**	**0.05**	0.95	0.22	0.95	0.15
	0.15	0.96	0.33	0.89	0.00		**0.25**	0.94	0.10	0.94	0.09
	0.25	0.94	0.10	0.95	0.16		**0.75**	0.98	0.93	0.78	0.00
	0.55	0.97	0.64	0.83	0.00		**0.95**	0.97	0.58	0.91	0.02
	0.65	0.96	0.33	0.89	0.01	**0.60**	**0.15**	0.90	0.01	0.49	0.00
	0.85	0.97	0.54	0.95	0.16		**0.55**	0.96	0.24	0.88	0.00
	0.95	0.96	0.30	0.21	0.00		**0.85**	0.94	0.12	0.86	0.00
	1.05	0.98	0.75	0.99	0.99		**1.15**	0.91	0.02	1.00	1.00
	1.15	0.93	0.06	0.95	0.19	**0.70**	**0.05**	0.75	0.00	0.89	0.00
0.20	**0.05**	0.82	0.00	0.91	0.02		**0.35**	0.94	0.07	0.90	0.01
	0.25	0.93	0.07	0.90	0.01		**0.75**	0.97	0.44	0.72	0.00
	0.35	0.93	0.05	0.97	0.65		**1.05**	0.92	0.04	1.00	1.00
	0.55	0.92	0.02	0.89	0.00	**0.80**	**0.05**	0.84	0.00	0.87	0.00
	0.75	0.92	0.03	0.81	0.00		**0.35**	0.95	0.17	0.93	0.04
	0.95	0.74	0.00	0.90	0.01		**0.75**	0.89	0.00	1.00	1.00
	1.15	0.87	0.00	0.87	0.00		**1.05**	0.86	0.00	1.00	1.00
0.30	**0.05**	0.95	0.22	0.93	0.04	**0.90**	**0.05**	0.93	0.05	0.89	0.01
	0.25	0.94	0.07	0.90	0.01		**0.35**	0.98	0.93	0.87	0.00
	0.45	0.88	0.00	0.83	0.00		**0.65**	0.93	0.05	1.00	1.00
	0.75	0.97	0.42	0.88	0.00		**1.05**	0.90	0.01	1.00	1.00
	0.95	0.94	0.09	0.85	0.00	**1.00**	**0.05**	0.90	0.04	0.70	0.00
	1.15	0.94	0.08	0.90	0.01		**0.45**	0.93	0.16	0.63	0.00
0.40	**0.05**	0.96	0.30	0.97	0.53		**0.65**	0.97	0.81	1.00	1.00
	0.35	0.83	0.00	0.95	0.19		**0.95**	0.94	0.30	1.00	1.00
	0.65	0.96	0.29	0.93	0.06	**1.10**	**0.05**	0.94	0.28	0.86	0.00
	0.95	0.97	0.58	0.91	0.02		**0.55**	0.88	0.02	1.00	1.00
	1.15	0.95	0.16	0.84	0.00		**1.05**	0.94	0.23	1.00	1.00

Table 12: Statistics and p-values from Shapiro-Wilk normality tests on run results for action and coordination costs. Results show great disparity of p-values. High action or coordination costs (or both) result in simulations not reaching full consistency and therefore all runs showing the same maximum value of 150,000 interactions. Results suggest that we should be sceptical of supposing an underlying distribution for the process and differences should be tested by means of non-parametric methods.

where U_i is the test statistic for the sample of interest, n_1 is the number of values for the first sample, n_2 the number of values for the second sample, and ΣR_i is the sum of the ranks for the sample of interest.

To compute whether the U statistic lies within the critical region a z-score is obtained using formulas 25 26 and 27.

$$\bar{x}_u = \frac{n_1 n_2}{2} \tag{25}$$

where $\bar{x}_U$ is the mean, n_1 is the number of samples from the first population and n_2 is the number of samples from the second population.

$$S_U = \sqrt{\frac{n_1 n_2 (n_1 + n_2 + 1)}{12}} \tag{26}$$

where S_U is the standard deviation.

$$z^* = \frac{U_i - \bar{x}_U}{S_U} \tag{27}$$

where z^* is the z-score for a normal approximation and U_i is the U statistic for the sample of interest.

A commonly used effect size to determine the degree of association between groups can be calculated by:

$$ES = \frac{|z|}{\sqrt{n}} \tag{28}$$

where $|z|$ is the absolute value of the z-score and n is the total number of observations.

syntactic category	semantic dimensions
S:	*shape + colour + direction*
A:	*direction*
B:	*shape + colour*
E:	*colour*
F:	*shape + direction*
G:	*shape*
H:	*colour + direction*

Table 13: Syntactic dimensions of the common language developed by a group of interacting altruistic agents.

A.3 COMMON LANGUAGE

Displayed on table 14 is a common language that emerged in one of the simulations of interaction within a group of altruistic agents. Here the action cost ($c_a = 0.55$) while the coordination cost ($c_c = 0.50$). The second column shows a rule's syntactic category, whose semantic dimensions are listed in table 13. The key-value dictionary of syntactic categories is shared by all agents, though the pairing is different at each simulation, since categories and semantic content are linked as the need arises: a new syntactic category is required whenever an agent chunks a previous rule and assigns meaning to the parts. If the combination of semantic dimensions is new to the group, then a new syntactic new is assigned to it.
Table 15 depicts the maximally weighted rules for all agents.

Table 14: Common language of group of altruistic agents.

	syntax	symbols	semantic		syntax	symbols	semantic
1	S $\rightarrow$	E·A·G	[circle, square, right, left, green, red]	20	A $\rightarrow$	"t"	[right]
2	S $\rightarrow$	G·A·E	[circle, square, right, left, green, red]	21	S $\rightarrow$	"ozegli"	[square, right, red]
3	S $\rightarrow$	G·E·A	[circle, square, right, left, green, red]	22	S $\rightarrow$	"ntfpnobxr"	[square, right, green]
4	S $\rightarrow$	H·G	[circle, square, right, left, green, red]	23	G $\rightarrow$	"p"	[square]
5	S $\rightarrow$	E·F	[circle, square, right, left, green, red]	24	E $\rightarrow$	"m"	[green]
6	S $\rightarrow$	G·H	[circle, square, right, left, green, red]	25	G $\rightarrow$	"e"	[circle]
7	S $\rightarrow$	B·A	[circle, square, right, left, green, red]	26	E $\rightarrow$	"r"	[red]
8	B $\rightarrow$	G·E	[circle, square, green, red]	27	A $\rightarrow$	"y"	[right]
9	B $\rightarrow$	E·G	[circle, square, green, red]	28	S $\rightarrow$	"rfe"	[circle, left, red]
10	H $\rightarrow$	E·A	[right, left, green, red]	29	S $\rightarrow$	"iwl"	[circle, left, green]
11	H $\rightarrow$	A·E	[right, left, green, red]	30	S $\rightarrow$	"m"	[square]
12	F $\rightarrow$	G·A	[circle, square, right, left]	31	E $\rightarrow$	"f"	[red]
13	G $\rightarrow$	"t"	[circle]	32	S $\rightarrow$	"iehh"	[square, left, green]
14	E $\rightarrow$	"y"	[green]	33	G $\rightarrow$	"r"	[circle]
15	A $\rightarrow$	"e"	[left]	34	H $\rightarrow$	"yt"	[right, green]
16	E $\rightarrow$	"n"	[red]	35	A $\rightarrow$	"g"	[right]
17	G $\rightarrow$	"s"	[square]	36	S $\rightarrow$	"eyt"	[circle, right, green]
18	A $\rightarrow$	"s"	[right]	37	H $\rightarrow$	"ft"	[right, red]
19	A $\rightarrow$	"f"	[left]	38	A $\rightarrow$	"r"	[left]

39	G $\rightarrow$	"g"	[circle]
40	E $\rightarrow$	"s"	[green]
41	H $\rightarrow$	"mphsg"	[left, green]
42	E $\rightarrow$	"s"	[red]
43	A $\rightarrow$	"d"	[left]
44	F $\rightarrow$	"ro"	[circle, left]
45	E $\rightarrow$	"g"	[green]
46	B $\rightarrow$	"ms"	[square, red]
47	F $\rightarrow$	"t"	[circle, right]
48	G $\rightarrow$	"f"	[circle]
49	B $\rightarrow$	"op"	[circle, green]
50	S $\rightarrow$	"snt"	[circle, right, red]
51	F $\rightarrow$	"yt"	[circle, right]
52	S $\rightarrow$	"tnvhwmdx"	[circle, right, red]
53	S $\rightarrow$	"aqk"	[circle, right, red]
54	A $\rightarrow$	"m"	[right]
55	S $\rightarrow$	"ffbsqezp"	[square, left, red]
56	B $\rightarrow$	"tn"	[circle, red]
57	H $\rightarrow$	"ns"	[right, red]
58	B $\rightarrow$	"sn"	[square, red]
59	S $\rightarrow$	"syziwf"	[square, left, green]
60	B $\rightarrow$	"sy"	[square, green]
61	S $\rightarrow$	"nes"	[square, left, red]
62	S $\rightarrow$	"nst"	[circle, right, red]
63	F $\rightarrow$	"ts"	[square, right]
64	S $\rightarrow$	"yst"	[circle, right, green]
65	S $\rightarrow$	"ytt"	[circle, right, green]
66	F $\rightarrow$	"ss"	[square, right]
67	S $\rightarrow$	"ntt"	[circle, right, red]
68	S $\rightarrow$	"syt"	[circle, right, green]
69	S $\rightarrow$	"ttn"	[circle, right, red]
70	S $\rightarrow$	"stn"	[circle, right, red]
71	S $\rightarrow$	"esn"	[square, left, red]
72	S $\rightarrow$	"nse"	[circle, right, red]
73	S $\rightarrow$	"tty"	[circle, right, green]
74	S $\rightarrow$	"sty"	[circle, right, green]
75	S $\rightarrow$	"str"	[circle, right, red]
76	S $\rightarrow$	"nfs"	[square, left, red]

77	S →	"myt"	[circle, right, green]
78	F →	"ts"	[circle, right]
79	F →	"tt"	[circle, right]
80	S →	"yfs"	[square, left, green]
81	S →	"eys"	[square, left, green]
82	S →	"mmphsg"	[square, left, green]
83	S →	"esy"	[square, left, green]
84	S →	"mft"	[circle, left, green]
85	S →	"etr"	[circle, left, red]
86	S →	"ety"	[circle, left, green]
87	S →	"mro"	[circle, left, green]
88	H →	"nf"	[left, red]
89	S →	"etn"	[circle, left, red]
90	S →	"ssy"	[square, right, green]
91	S →	"yts"	[square, right, green]
92	E →	"t"	[red]
93	S →	"tsn"	[square, right, red]
94	S →	"ssn"	[square, right, red]

Table 15: Agents' maximally weighted rules

		number	syntax	symbol	semantic values	weight
agent 1	0	R 0	S →	A·G·E	[circle, square, right, left, green, red]	1.000000
	12	R 12	F →	A·G	[circle, square, right, left]	1.000000
	18	R 18	G →	"t"	[circle]	1.000000
	19	R 20	E →	"y"	[green]	1.000000
	20	R 19	G →	"s"	[square]	1.000000
	21	R 22	A→	"e"	[left]	1.000000
	22	R 21	E →	"n"	[red]	1.000000
	23	R 23	A →	"s"	[right]	1.000000
	26	R 26	S →	"ozegli"	[square, right, red]	0.999998
	27	R 27	S →	"ntfpnobxr"	[square, right, green]	0.999860
	30	R 30	S →	"rfe"	[circle, left, red]	0.998100
	39	R 39	S →	"eyt"	[circle, right, green]	0.982960
	40	R 40	S →	"iehh"	[square, left, green]	0.902291
	44	R 43	S →	"iwl"	[circle, left, green]	0.945128
	56	R 55	S →	"ffbsqezp"	[square, left, red]	0.998458
	82	R 81	F →	"mphsg"	[square, left]	0.995526
	83	R 82	S →	"aqk"	[circle, right, red]	0.990622
agent 2	0	R 0	S→	A·G·E	[circle, square, right, left, green, red]	1.000000
	18	R 18	E →	"y"	[green]	1.000000
	19	R 19	G →	"t"	[circle]	1.000000
	20	R 21	A →	"e"	[left]	1.000000
	21	R 20	G →	"s"	[square]	1.000000
	22	R 22	E →	"n"	[red]	1.000000
	23	R 23	A →	"s"	[right]	1.000000
	27	R 26	S →	"ozegli"	[square, right, red]	1.000000
	28	R 28	B →	"tfpnobxr"	[square, green]	0.999835
	32	R 32	H →	"yt"	[right, green]	0.999937
	35	R 35	F→	"t"	[circle, right]	0.996042
	37	R 37	S →	"ffbsqezp"	[square, left, red]	0.998548
	40	R 40	S →	"rfe"	[circle, left, red]	0.967260
	43	R 43	B →	"op"	[circle, green]	0.998467
	86	R 86	B →	"tanejfhru"	[circle, red]	0.991345
	87	R 87	F →	"mphsg"	[circle, left]	0.959639

		number	syntax	symbol	semantic values	weight
agent 3	0	R 0	S →	A·G·E	[circle, square, right, left, green, red]	1.000000
	18	R 19	G →	"t"	[circle]	1.000000
	19	R 20	A →	"e"	[left]	1.000000
	20	R 18	G →	"s"	[square]	1.000000
	21	R 21	E →	"y"	[green]	1.000000
	22	R 24	E →	"n"	[red]	1.000000
	23	R 23	A →	"s"	[right]	1.000000
	26	R 26	S →	"ozegli"	[square, right, red]	0.999992
	27	R 28	S →	"ntfpnobxr"	[square, right, green]	0.999698
	38	R 38	S →	"iwl"	[circle, left, green]	0.913422
	40	R 39	B →	"rf"	[circle, red]	0.931200
	44	R 43	H →	"mphsg"	[left, green]	0.991306
	51	R 51	S →	"ffbsqezp	[square, left, red]	0.997423
	52	R 52	H →	"sn"	[right, red]	0.990095
	67	R 67	H →	"uyqldu"	[right, green]	0.994088
	90	R 90	H →	"anejfhrud"	[left, red]	0.998508
agent 4	0	R 0	S →	A·G·E	[circle, square, right, left, green, red]	1.000000
	18	R 18	G →	"t"	[circle]	1.000000
	19	R 19	E →	"y"	[green]	1.000000
	20	R 20	A →	"e"	[left]	1.000000
	21	R 21	G →	"s"	[square]	1.000000
	22	R 22	E →	"n"	[red]	1.000000
	23	R 23	A →	"s"	[right]	1.000000
	25	R 25	S →	"ozegli"	[square, right, red]	0.999939
	26	R 26	S →	"ntfpnobxr"	[square, right, green]	0.999832
	33	R 33	S →	"rfe"	[circle, left, red]	0.995783
	36	R 36	B →	"rf"	[circle, red]	0.983187
	44	R 44	S →	"iwl"	[circle, left, green]	0.920450
	49	R 49	H →	"sn"	[right, red]	0.982922
	56	R 56	H →	"mphsg"	[left, green]	0.995160

		number	syntax	symbol	semantic values	weight
agent 5	0	R 0	S →	A·G·E	[circle, square, right, left, green, red]	1.000000
	18	R 18	G →	"t"	[circle]	1.000000
	19	R 19	E →	"y"	[green]	1.000000
	20	R 20	A →	"e"	[left]	1.000000
	21	R 21	G →	"s"	[square]	1.000000
	22	R 22	E →	"n"	[red]	1.000000
	23	R 23	A →	"s"	[right]	1.000000
	25	R 25	S →	"ozegli"	[square, right, red]	0.999939
	26	R 26	S →	"ntfpnobxr"	[square, right, green]	0.999832
	33	R 33	S →	"rfe"	[circle, left, red]	0.995783
	36	R 36	B →	"rf"	[circle, red]	0.983187
	44	R 44	S →	"iwl"	[circle, left, green]	0.920450
	49	R 49	H →	"sn"	[right, red]	0.982922
	56	R 56	H →	"mphsg"	[left, green]	0.995160
agent 6	0	R 0	S →	A·G·E	[circle, square, right, left, green, red]	1.000000
	12	R 12	H →	E·A	[right, left, green, red]	1.000000
	18	R 18	G →	"t"	[circle]	1.000000
	19	R 19	A →	"e"	[left]	1.000000
	20	R 21	E →	"y"	[green]	1.000000
	21	R 22	G →	"s"	[square]	1.000000
	22	R 23	E →	"n "	[red]	1.000000
	23	R 20	A →	"s"	[right]	1.000000
	25	R 26	S →	"ozegli"	[square, right, red]	1.000000
	26	R 27	S →	"ntfpnobxr"	[square, right, green]	0.999835
	30	R 29	B →	"rf"	[circle, red]	0.999145
	33	R 32	H →	"yt"	[right, green]	0.997884
	41	R 40	S →	"iwl"	[circle, left, green]	0.942288
	77	R 77	S →	"rfe"	[circle, left, red]	1.000000
	78	R 78	F →	"ts"	[square, right]	0.995115
	89	R 89	H →	"anejfhrud"	[left, red]	0.992830

		number	syntax	symbol	semantic values	weight
agent 7	0	R 2	S →	A·G·E	[circle, square, right, left, green, red]	1.000000
	2	R 0	S →	E·G·A	[circle, square, right, green, red]	1.000000
	5	R 5	S →	A·E·G	[circle, square, left, green, red]	1.000000
	12	R 12	H →	A·E	[right, left, green, red]	1.000000
	19	R 22	E →	"y"	[green]	1.000000
	20	R 21	A →	"e"	[left]	1.000000
	21	R 20	G →	"s"	[square]	1.000000
	22	R 24	E →	"n"	[red]	1.000000
	23	R 19	A →	"t"	[right]	1.000000
	24	R 23	G →	"t"	[circle]	0.999967
	27	R 27	S →	"ozegli"	[square, right, red]	1.000000
	33	R 32	B →	"rf"	[circle, red]	0.999676
	38	R 38	S →	"iwl"	[circle, left, green]	0.941433
	42	R 42	H →	"sn"	[right, red]	0.964153
	71	R 71	S →	"eyt"	[circle, right, green]	0.985516
agent 8	0	R 0	S →	A·G·E	[circle, square, left, green, red]	1.000000
	9	R 19	A →	"e"	[left]	1.000000
	20	R 20	G →	"t"	[circle]	1.000000
	21	R 21	G →	"s"	[square]	1.000000
	22	R 22	E →	"y"	[green]	1.000000
	23	R 23	E →	"n"	[red]	1.000000
	24	R 24	A →	"s"	[right]	1.000000
	27	R 27	S →	"ozegli"	[square, right, red]	0.999990
	28	R 28	B →	"rf"	[circle, red]	0.999425
	29	R 29	S →	"ntfpnobxr"	[square, right, green]	0.999137
	41	R 41	S →	"iwl"	[circle, left, green]	0.998400
	43	R 43	S →	"iehh"	[square, left, green]	0.927233
	48	R 48	B →	"ffbsqez"	[square, red]	0.999610
	49	R 49	B →	"sm"	[square, green]	0.997977
	62	R 62	S →	"ffbsqezp"	[square, left, red]	0.993623

		number	syntax	symbol	semantic values	weight
agent 9	0	R 1	S→	A·G·E	[circle, square, right, left, green, red]	1.000000
	19	R 19	A →	"e"	[left]	1.000000
	20	R 20	G →	"t"	[circle]	1.000000
	21	R 22	E →	"y"	[green]	1.000000
	22	R 23	E →	"n"	[red]	1.000000
	23	R 21	A →	"s"	[right]	1.000000
	24	R 27	G →	"s"	[square]	1.000000
	27	R 28	S →	"ozegli"	[square, right, red]	0.999998
	30	R 30	S →	"ntfpnobxr"	[square, right, green]	0.999903
	39	R 38	S →	"eyt"	[circle, right, green]	0.997824
	46	R 43	S →	"ffbsqezp"	[square, left, red]	0.997579
	49	R 48	H →	"mphsg"	[left, green]	0.997534
	50	R 49	H →	"yt"	[right, green]	0.941448
	55	R 55	S →	"iehh"	[square, left, green]	0.993389
agent 10	0	R 1	S →	A·G·E	[circle, square, right, left, green, red]	1.000000
	10	R 10	S →	A·B	[circle, square, right, green, red]	1.000000
	12	R 12	B →	G·E	[circle, square, green, red]	1.000000
	18	R 18	G →	"t"	[circle]	1.000000
	19	R 19	E →	"y"	[green]	1.000000
	20	R 23	A →	"e"	[left]	1.000000
	21	R 20	E →	"n"	[red]	1.000000
	22	R 22	G →	"s"	[square]	1.000000
	23	R 21	A →	"s"	[right]	1.000000
	26	R 28	S →	"ozegli"	[square, right, red]	1.000000
	27	R 26	S →	"ntfpnobxr"	[square, right, green]	0.999888
	34	R 34	H →	"ffbsqez"	[left, red]	0.999750
	36	R 35	S →	"rfe"	[circle, left, red]	0.997383
	38	R 38	S →	"iwl"	[circle, left, green]	0.973665
	58	R 55	H →	"mphsg"	[left, green]	0.995123
	74	R 74	S →	"snt"	[circle, right, red]	0.989273

Agents' maximally weighted rules

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